# Sourcing with Differentiated Supply Bases

by

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A dissertation submitted in partial fulfillment
of the requirements for the degree of
Doctor of Philosophy
(Industrial and Operations Engineering)
in The University of Michigan
2014

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To Meaghan and the rest of my family

## ACKNOWLEDGEMENTS

I would like to thank my advisors, Damian Beil and Izak Duenyas, for their time, support, and valued feedback during my time as a student at Michigan. Many thanks to Xiuli Chao, whose courses and research discussions always proved interesting and enlightening. Steve Leider's excellent intuition and guidance provided great support for the experimental portions of my research that is contained in the fourth chapter of this dissertation.

I am extremely grateful for the excellent staff that supported me in the Industrial and Operations Engineering department, especially Matt Irelan, Tina Picano Sroka, Chris Konrad, Mint, and Candy Ellis. Two funding sources, the National Science Foundation Graduate Research Fellowship and the STIET Fellowship (NSF IGERT grant 0654014), provided excellent support during my studies.

I developed many great friendships at Michigan that made my time here enjoyable. Marcial Lapp and Greg King provided great support as a wonderful roommate and officemate, respectively. Many thanks to Jonathan Helm, Jivan Deglise-Favre-Hawkinson, and Brian Cook for their willingness to obsess over Michigan football and basketball, which always provided a great outlet for lively discussions. Thanks also go to Chardson, Kat and Chris, Kathryn and Joho, Sara and Robert, Arleigh, and Fred for being great friends along the Ph.D. journey.

My family's support and reassurance has guided me to where I am today. My mom, Cindy, is always willing to listen, offer assurance, and goes to great lengths to help me at the drop of a hat. Thanks goes to my father, David, whose tendency for inquisitive, thoughtful reasoning helped spark my desire to keep diving deeper into my interests. Thanks to my brother, Evan, for always pushing me to excel — and putting up with my antics as teenagers.

Finally, for Meaghan's unwavering support and strength: I am forever grateful, and thanks for always being there for me despite the distance, stress, and my unique sense of humor.

# TABLE OF CONTENTS

# LIST OF FIGURES

**Figure**

# LIST OF TABLES

**Table**

## ABSTRACT

This dissertation studies two research problems in the field of sourcing. Both topics address sourcing considerations when the buyer's potential supplier base consists of incumbent and entrant suppliers. The first topic examines when a buyer seeking to procure multiple units of an input may find it advantageous to run a "test auction" where she has incumbents bid on a portion of the desired units. The test auction reveals incumbent cost information that helps the buyer determine how many entrants to recruit at a cost prior to awarding the remaining units. The optimal number of entrant suppliers to recruit follows a threshold policy that is monotonic in the test auction's clearing price unless the underlying supplier cost distribution is not regular. When the buyer uses a reserve price, supplier recruitment can serve as the buyer's "outside option:" If the reserve price is not met in the test auction, the buyer recruits new suppliers and runs a second auction. The attractiveness of the test auction procedure is compared relative to the more conventional approach in which the buyer auctions off her entire demand in one auction. Finally, the optimal mechanism is designed and a numerical study shows that the test with reserve price strategy performs well given its ease of implementation.

The second topic surrounds the cost information asymmetry that arises when an entrant competes against an incumbent supplier, and is studied both theoretically and experimentally. The entrant's cost uncertainty complicates his ability to bid in an auction against an incumbent who is more knowledgeable regarding her costs

due to her experience with the buyer. The entrant's ability to resolve this cost uncertainty by incurring a learning fee is studied. The entrant follows a threshold learning strategy that depends on the nature of the unknown cost distribution. The entrant's bidding strategy and the buyer-optimal learning fee are analyzed. The experiment shows that subjects understand the basic intuition but tend to under-learn and bid too aggressively when they do not learn prior to bidding; this suggests that buyers need not expend as much effort to reduce the entrant's learning fee as theory predicts.

# CHAPTER I

## Introduction

This dissertation studies two topics in sourcing with differentiated suppliers. As sourcing is a relatively recently-emerging field in operations management, much of the current research is based upon assumptions that are not applicable in many practical situations; one such assumption is that all suppliers are homogeneous. The goal of this dissertation is to address two important research problems that stem from one of the most basic distinctions among suppliers: their previous experience supplying the buying firm. Throughout the dissertation, we refer to suppliers who have already been recruited by the buyer or previously supplied the buyer with the item currently being sourced as an *incumbent supplier*, and those who have not supplied the buyer as a potential *entrant supplier*. The fundamental differences between these two groups of suppliers lead to various considerations when a buyer is designing her sourcing strategy.

The two research problems address a buyer sourcing an item from a supplier pool consisting of both types of suppliers. We blend different approaches of analyzing each research problem with the overall goal of providing managerial-level insights; theoretical, numerical, and experimental methods are used in the two research topics. In each of the problems, we first develop a mathematical model that allows us to analyze the buyer and suppliers' optimal behaviors. In both cases, we primarily use a second-price auction setting to formally model the competitive bidding process. Due to the analytical nature of such research, we aim to build intuition that can illuminate intelligent sourcing mechanisms.

In the topic covered in Chapter II, titled "When to Deploy Test Auctions in Sourcing," we study a buyer who is seeking to procure a large quantity of an item and has the costly option of recruiting entrant suppliers to compete with the incumbent suppliers for the contract. We claim that, under certain conditions, the buyer can benefit from using a novel "test auction" sourcing method. The motivation behind the test auction stems from practical concerns: When the recruitment process of entrant suppliers is time-consuming and costly, a buyer may want to gain a better understanding of the pricing in the incumbent market before deciding how many entrants to recruit. After modeling and analyzing this problem from a theoretical standpoint, we then illustrate the test auction strategy's performance through numerical examples and benchmarking against the optimal mechanism.

The second topic ("Entrant Cost Uncertainty and Pre-Auction Learning") is studied from both theoretical and experimental perspectives in Chapters III and IV, respectively. For this research problem, we address the cost information asymmetry that can arise when an entrant supplier competes against an incumbent supplier who has previously produced the part for the buyer. Namely, if an incumbent supplier has experience supplying the buyer with the good or service, the incumbent may be more knowledgeable regarding her costs than an entrant supplier who wishes to compete to fulfill the contract. The entrant's cost uncertainty complicates his ability to bid in an auction against the better-informed incumbent supplier. We model the case where the entrant can choose to resolve this cost uncertainty by incurring a learning fee (e.g., hiring a consultant, holding a test production run, etc.). We theoretically analyze when the entrant would incur the fee to learn about his costs prior to competing against the incumbent, and find the entrant's bid conditional on his decision. We also model the buyer's ability to make it easier for the entrant to learn his costs and find the buyer's optimal strategy. We then design an experimental study to test subjects' behaviors in a laboratory setting. This allows us to identify which aspects of our theoretical results are robust in practice, and which aspects lead to unexpected behavior by subjects — and therefore might also lead to suboptimal decision-making by practitioners.

The remainder of this dissertation is organized as follows: In Chapter II, we study the "test auction" sourcing method. In Chapter III, the costly information acquisition problem is introduced and theoretical results are discussed. Chapter IV details how the costly information acquisition problem is tested in a controlled laboratory setting and provides the results and insights from the experiment. We conclude in Chapter V.

# CHAPTER II

# When to Deploy Test Auctions in Sourcing

## 2.1 Introduction

The average US manufacturer spends close to 60% of their revenues on purchases from outside suppliers (United States Department of Commerce, 2011). Intense competition has forced companies to find cost advantages in procurement. To this end, many firms have expanded their use of competitive bidding, whereby suppliers fiercely compete against each other in a "reverse auction" in order to win the buyer's business.

In this chapter we address the following question: How many bidders should a buyer recruit for a competitive bidding event? Surprisingly, most research on auctions takes the existence of bidders as their point of departure. It is clear that firms may want more bidders as the increased competition may result in better prices. However, it is not necessarily simple to identify new potential bidders.

Recently the authors worked with a Fortune 500 manufacturer who wanted to identify new potential suppliers. The manufacturer (the buyer) conducted an extensive search for potential suppliers for a certain part. The part is used in highly engineered applications and is produced by high tolerance milling of bar stock on multi-spindle lathes. The buyer gathered supplier names by scouring various sources, including library and industry databases, web searches, and other business units within the firm. They also contacted multi-spindle lathe manufacturers to get customer lists. After searching the globe for suppliers, and discarding those who were too small or lacked ultrasonic washing capabilities (the parts themselves needed to be extremely clean to be usable in the buyer's assembly processes), the buyer was left with a handful of new prospective suppliers.

The approaches a buyer can use to recruit prospective suppliers are not limited to identifying existing suppliers, but could involve identifying novel sources: At the buyer firm we interacted with, for parts the buyer firm typically bought from bar stock finishers, suppliers capable of manufacturing parts out of cold-headed blanks instead of bar stock were also considered for part segments where the material and geometry allowed a near net shape blank to be cold headed and then finished through machining. Buyers can also draw on third party service providers — a large cottage industry of firms exists to help buyers identify potential suppliers. Trading on their knowledge and familiarity with suppliers and their capabilities, these firms provide interested buyer firms with a prospective supplier list, in return for a fee.

Since recruiting new suppliers entails costs for the buyer (in tracking down prospective suppliers, identifying novel sources, or paying a third party), the decision of how many bidders to recruit for the auction is not trivial: The number of suppliers to include in an auction should balance the benefits the buyer anticipates from intensified bidding competition with the costs of recruiting more suppliers who can produce the goods the buyer desires.

In fact, the buyer firm we worked with had a few existing suppliers ("incumbents") already in the supply base who they knew were capable of making the part. This is because the suppliers had made similar parts in the past. However, the fact that they may have made similar parts in the past does not mean that the buyer will know how much the supplier will charge for a new part — changes in specifications, supplier utilization, and economic factors can significantly affect costs. Moreover, the buyer decided to recruit new suppliers ("entrants") in order to heat up competition for producing the part and drive down pricing. The buyer eventually ran a reverse auction for the parts, with some contracts going to incumbents and some going to entrants.

After observing the above, and contemplating the time and resources that a buyer invests in recruiting suppliers, we were left wondering if there could be a way to manage these supplier recruitment costs. In fact, given how simple it is to run a reverse auction, a buyer firm could potentially auction off a portion of her demand in order to gain a better understanding of the pricing in the incumbent market (whether it is very competitive or not), and based on this determine how many new suppliers to recruit. Although this is a very natural question that would arise in a variety of industries and settings (after all, exerting time and effort to recruit new suppliers is something that many buyers do prior to competitive bidding events), we could find little prior research addressing it. Filling this gap is the goal of this chapter.

Other papers have addressed the process of dealing with new suppliers once they have already been added to buyer's supply base. In the operations management literature, these papers typically deal with supplier qualification. The supplier qualification process refers to the act of verifying a potential suppliers' production abilities, history with previous customers, financial stability, and other attributes. The main distinction between new supplier recruitment and supplier qualification stems from a potential supplier's ability to place a competitive bid: not-yet-qualified suppliers could hypothetically place a bid before undergoing the qualification process; by contrast, in our case suppliers who have not been recruited yet are unable to bid because they are not aware of the auction and the buyer has not discovered them. The supplier qualification literature (e.g., Wan and Beil (2009) and Wan et al. (2012)) considers whether it is optimal to delay qualification screening until after the auction. In our model, the buyer cannot delay recruiting suppliers until after the auction, so the problems faced are fundamentally different. We focus on the idea of test auctions to inform the buyer's decision on how many suppliers to recruit.

Specifically, we model the following trade-off. To ensure competition and realize the lowest possible cost, a buyer ideally wants as many suppliers to compete for the contract as possible. However, because recruiting additional suppliers is expensive, the buyer faces a difficult decision. She can either absorb new supplier recruitment costs and recruit more suppliers to increase price competition, or instead she can choose not to add any additional suppliers to her supply base and hope that the existing suppliers can produce the input at a low cost. Usually the procurement process must be completed in a timely manner because once a buyer has decided to put a particular contract out for bid (e.g., because it won new business from an upstream customer), there is a limited time window within which the supplier(s) for the contract must be selected. To accommodate the time-consuming nature of the bid preparation process (e.g., understanding the product specifications, getting trained on the buyer auction software platform, etc.), for each contract, a buyer can usually perform one recruitment round whereby she recruits new suppliers who then prepare their bids in parallel.

Recognizing these complicating factors – the buyer who may already have a few existing incumbent suppliers needs to assess the benefit of recruiting additional suppliers against the costs – we examine the following approach when answering the question of how many bidders to recruit for an auction. The buyer may hold an initial auction, which we call a "test auction," for a portion of the units she needs in order to get pricing information from the existing supply base. Then, the buyer can use her updated knowledge about the existing suppliers to help her decide how many additional suppliers to recruit for a final auction in which the remainder of the units will be sourced. We note that it is fairly common for firms to pick a supplier, give them some business and consider them for additional business if their price performance meets firm targets. Several firms we have worked with already do this. Thus, our proposed mechanism would not be out of place in such environments. In our setting, the unsettled question resolved by the auction is cost/price performance. Thus, our paper takes two activities that are very common in practice — new supplier recruitment and competitive auctions for sourcing — and combines them in an innovative way to result in potential cost savings for buyers when sourcing.

In analyzing the buyer's problem, we answer the following research questions:

1. When is it a good strategy for the buyer to run a test auction versus recruit additional suppliers and run one auction for all units?

2. How many suppliers should the buyer recruit under each scenario and in the test auction scenario how does this decision depend on the outcome of the test auction? Furthermore, how can the buyer best implement a reserve price and how well do these strategies perform compared to the theoretically optimal (but perhaps hard to implement) mechanism (along the lines of Myerson (1981))?

3. How do cost distributions, the size of the minimal quantity that has to be auctioned, the number of incumbent suppliers, and other business factors affect

these decisions?

There has been a fair amount of literature on sourcing policies that address both auctions and other types of contracting mechanisms; Elmaghraby (2000) provides a good review. The main contribution of our paper is the novel "test auction" procedure, where the buyer may choose to use sequential auctions separated by a new supplier recruitment round. The test auction serves as a partial cost-discovery mechanism which the buyer uses to inform her decision regarding how many entrants suppliers should be added to the supply pool to compete in a subsequent auction. Peleg et al. (2002) study a setting where the buyer chooses how many suppliers to recruit for an auction, but they do not study the possibility that the buyer runs a test auction to update her information about existing suppliers, which is our focus. de Boer et al. (2000) find the "Economic Tender Quantity" when there are costs associated with sending RFQs, evaluating suppliers' tenders, and communicating the results of the competition. In our model, we study the same type of cost, but incorporate incumbent suppliers and allow multiple auctions.

Many buyers split their contract among different suppliers. Papers on multi-sourcing generally focus on mitigating supply disruption risks, e.g., Tomlin (2006), Federgruen and Yang (2009), Chaturvedi and Martínez-de-Albéniz (2011), Yang et al. (2012). Our buyer also can multi-source, but for an entirely different reason. In our paper, multi-sourcing can be a consequence of the buyer discovering information about the incumbents' costs.

To our knowledge, ours is the first paper to consider the use of test auctions to help manage new supplier recruitment and sourcing costs. Our paper should assist firms to better manage their total (contracting+new supplier recruitment) procurement costs.

## 2.2 Model

We model a risk-neutral, cost-minimizing buyer who seeks to procure $Q$ units of a certain input. For example, $Q$ could be in the tens or hundreds of thousands, corresponding to months or years of supply of a certain component. We initially assume that the contracts for these units will be awarded using open-bid descending-price procurement auctions, which proceed as follows: The auction price falls continuously until all but one bidder drops out; the last remaining bidder wins the auction and is paid the auction ending price. (Auctions with a continuously falling price are also known as "reverse clock auctions"; see Ausubel and Cramton (2006) for discussions about clock auctions in practice.) Of course, the buyer could use other mechanisms to award the contract. In §2.3.4, we will study the optimal mechanism that the buyer could use to award the contract. However, open-bid descending-price auctions are ubiquitous in practice and are easy to explain and implement. (In §2.4.1, we address the other common auction format, the first-price sealed-bid auction.)

We assume that whenever the buyer runs an auction she has to auction off at least $y$ units. Auctions for very small quantities may not generate much interest from suppliers and that is why we model a minimum purchase quantity. (For example, an auction to buy one standard bolt is not going to entice any suppliers to bid.) Different industries may have different minimum order quantities, and our model allows for any $0 \leq 2y \leq Q$ (if $Q < 2y$, a test auction is not feasible since the buyer's desired quantity $Q$ would be so small that she must auction off her entire order in a single auction).

We assume that there are two groups of suppliers: incumbent suppliers and as-of-yet-unknown potential suppliers. The *incumbent suppliers* can be viewed as suppliers whom the buyer has recruited in the past and thus further recruitment is unnecessary. This may be because the supplier has produced a previous generation of the product or has supplied a similar product. Companies we have worked with will typically have at most a few incumbents for any given part (e.g., there were only two incumbents for many parts at the buyer firm mentioned in the Introduction). We let $n$ denote the number of incumbent suppliers. There are also suppliers who are as-of-yet unknown; we call these *potential* or *entrant suppliers.* To recruit these suppliers, the buyer incurs a cost. For example, the cost may stem from scouring the globe for existing suppliers, developing novel sources, or paying a third party a finder's fee. The expected cost to recruit $m$ entrant suppliers is $k(m)$. We assume that $k(\cdot)$ is an increasing convex (possibly weakly convex) function. This captures the fact that each successive entrant is typically more costly for the buyer to identify because the buyer will exhaust the most cost-effective avenues of recruitment first. Further, we assume that $k(1) > 0$ — that is, the buyer cannot recruit an entrant for free (alternatively, cases where $k(1) = 0$ can be handled by our model by considering the entrants who cost zero for the buyer to recruit as incumbent suppliers).

As is common in the literature (e.g., Chen (2007)) we assume each supplier $i$ is risk-neutral and has a linear production cost function $x_i \cdot q$, where $q$ is the number of units to be produced. The $x_i$'s are independent and identically distributed random variables with cumulative distribution $F$, probability distribution $f$, and support $[a, b]$. Further, we assume that the cost distribution $F$ is *regular* (i.e., $x + \frac{F(x)}{f(x)}$ is increasing in $x$), which is a common assumption in the auction literature. It is important to note that the new supplier recruitment process is aimed at identification of suppliers, not cost discovery. This is why the buyer needs to run an auction among the recruited suppliers for cost discovery. Each supplier's variable cost $x_i$ is their private information, but the distribution $F$ is common knowledge. We assume that the buyer must transact with a supplier; this captures cases where the buyer is purchasing a component that is needed in order to assemble her products, but the buyer does not have in-house production capabilities for the component.

In general once a buyer has decided to put a particular contract out for bid, there is a limited time window within which new contracts must be struck. To accommodate the fact that time is required for entrant suppliers to be identified, understand the buyer's specifications, get trained on the buyer's auction software platform, etc., within the sourcing time window we are considering the firm can only recruit suppliers once (although the firm can recruit multiple, $m$, entrant suppliers in parallel). This eliminates the possibility of the buyer spending many months identifying and waiting while an entrant prepares to bid in an initial auction, then spending many more months doing the same for a second entrant followed by a second auction, then spending many more months for a third entrant, etc. Such a "sequential screening" setting has been studied in McAfee and McMillan (1988), but the common practical setting that we are studying allows for recruitment only once during the procurement cycle.

### 2.2.1 Main Trade-Off

The buyer must decide if she wants to (i) recruit additional entrant suppliers up-front or (ii) auction a portion of the units among the incumbent suppliers to inform her decision regarding how many entrants to recruit, and then procure the remaining units through a subsequent auction. On the one hand, the first option increases competition for all the units. However, this may not be optimal for the buyer. One can imagine that if the buyer auctions off a subset of the units before recruiting any entrants, she may discover important cost information about the incumbent suppliers. If the incumbent suppliers' cost realizations are small, then spending additional money to recruit entrant suppliers is not as attractive as it was ex ante, and thus recruitment costs could be saved. Likewise, if the buyer discovers that the incumbent suppliers have relatively high costs, she may choose to recruit *more* entrant suppliers than she would have prior to discovering this information. Thus, deploying an initial auction for a subset of the units informs the buyer's decision regarding how many additional suppliers to recruit. However, with the test auction approach, the buyer may end up paying a high price for the units she buys in the first auction, while recruiting additional suppliers before running this auction would have resulted in potentially lower prices for these units. This is an interesting trade-off that has not been previously studied.

First we note that *if* the buyer decides to recruit some entrant suppliers prior to holding any auctions, she would just hold a single auction for all $Q$ units. This is because the buyer will not be able to initiate a second recruitment round and the competing suppliers all have linear cost structures. We will call this strategy the **no-test strategy**.

Conversely, we will call the case where the buyer holds an initial auction with the $n$ incumbent suppliers to inform her decision regarding how many entrant suppliers to recruit for a second auction for the remaining units the **test strategy**. We assume the buyer uses the clearing price of the first auction as a cap on the per-unit bids that the buyer will accept in the second auction. In essence, in the first auction, the auction price continuously descends until a single bidder remains in the auction. At this point, the price clock stops and the buyer recruits entrant suppliers to compete over the remaining units. When the second auction begins, the price clock continues to descend from the price at which the clock stopped, i.e. the clearing price of the first auction. As would be natural, we also assume that if the clearing price of the first auction is sufficiently low, the buyer may choose to source all $Q$ units from the winning incumbent supplier at that price. Given our model of the test strategy, it is optimal for the buyer to hold a single $y$-unit auction prior to recruitment (guaranteeing that the buyer spends the minimal amount in order to learn about the incumbents' costs) and then hold a single auction afterwards for the remaining $Q - y$ units (see Proposition II.1).

Figures 2.1 and 2.2 depict the timeline for the test and no-test strategies, respectively. $X_{(i:j)}$ denotes the $i^{\text{th}}$-lowest value among $j$ independent draws from distribution $F$ (in the figures "bidder $(i : j)$" refers to the bidder with the $i^{\text{th}}$ lowest cost among $j$ bidders). Having described the main trade-offs, we now move to addressing the research questions posed in the Introduction.

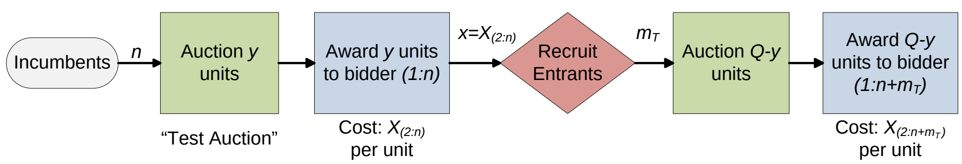



Figure 2.1: Timeline of the test strategy.

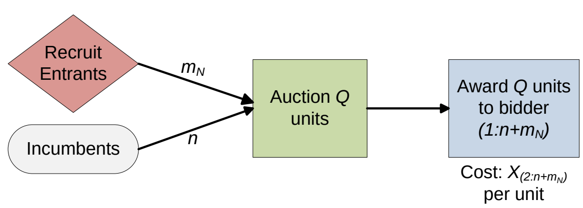



Figure 2.2: Timeline of the no-test strategy.

## 2.3 Analysis

In this section, we first formulate the buyer's expected costs under the test and no-test strategies which will then enable us to characterize situations when one is preferred to the other.

### 2.3.1 The Test and No-Test Strategies

Under the test strategy, the buyer first holds an auction for the minimum order quantity ($y$ units) with only the incumbent suppliers, then determines how many additional suppliers to recruit, and lastly she auctions off the remaining $Q - y$ units where the opening bid is equal to the clearing price from the first auction. The buyer's per-unit payment for the first $y$ units is the second-lowest cost among the $n$ incumbent suppliers (Proposition II.1 below shows that in equilibrium suppliers remain in an auction until either winning or reaching their true cost, whichever happens first); hence, the expected cost of the first auction under the test strategy is $\mathbb{E}[X_{(2:n)}]y$. For convenience, we define $x$ as the realization of $X_{(2:n)}$, the clearing price of the test auction. Thus $x$ is also the opening bid of the second auction. After holding the initial auction, the buyer must decide how many additional suppliers to recruit. The cost information revealed in the test auction (specifically, the value of $x$) allows the buyer to make a more informed decision than she would if she did not hold a test auction. The expected cost of the second auction (including recruitment costs) when $m_T$ additional suppliers are recruited is

$$\mathbb{E}[X_{(2:n+m_T)}|X_{(2:n)} = x](Q - y) + k(m_T). \tag{2.1}$$

In equation (2.1) the expectation is written as the second-lowest among $n + m_T$ draws, conditioned on the fact that the outcome of the test auction (among the $n$ incumbents) was clearing price $x$. Note that this could be equivalently described as the expected cost from an auction that opens at price $x$, with one bidder whose cost is at most $x$ (the winning incumbent from the test auction) competing for the contract alongside $m_T$ entrants. We will use this type of conditioning throughout the paper. We let $m_T^*$ denote the minimizer of (2.1). Note that $m_T^*$ is actually a function of $x$, but for convenience we simply write $m_T^*$. The buyer's total *ex ante* expected cost under the test strategy is the (expected) sum of the two auction costs and the recruitment costs:

$$\mathbb{E}[X_{(2:n)}]y + \mathbb{E}\left[\mathbb{E}[X_{(2:n+m_T^*)}|X_{(2:n)} = x](Q-y) + k(m_T^*)\right]$$

(Buyer's expected cost under test).

If the buyer bypasses the test auction and selects the no-test strategy, she first chooses how many entrant suppliers to recruit, and then holds a single auction for $Q$ units. If the buyer qualifies $m_N$ additional suppliers, her expected cost (the sum of the auction payment and recruitment costs) is $\mathbb{E}[X_{(2:n+m_N)}]Q + k(m_N)$. Let $m_N^*$ denote the minimizer of this cost; the buyer's total *ex ante* expected cost under the no-test strategy is thus

$$\mathbb{E}[X_{(2:n+m_N^*)}]Q + k(m_N^*) \quad \text{(Buyer's expected cost under no-test).}$$

The structure of the test and no-test strategies is characterized by the following proposition (proofs for our results can be found in §2.6).

**Proposition II.1.** *In equilibrium, under the test and no-test strategies, suppliers in an auction will remain in it until either the price reaches their true cost or they win the auction, whichever happens first. Under the test strategy, it is optimal for the buyer to auction off $y$ units in the first auction and $Q-y$ units in the second auction. The buyer's total cost function under the test strategy is discrete convex in the number of entrant suppliers she recruits, $m_T$. Moreover, the optimal number of entrant suppliers to recruit, $m_T^*$, is nondecreasing in the realization of the unit clearing price of the first auction, $x = X_{(2:n)}$. Similarly, under the no-test strategy, the buyer's total cost function is discrete convex in the number of entrant suppliers she recruits, $m_N$.*

The proposition proves that the buyer's expected cost under both strategies is discrete convex in $m$, which simplifies the buyer's choice regarding the number of entrants to recruit (because if the buyer prefers recruiting $m$ entrant suppliers to recruiting $m+1$ entrant suppliers, she also prefers recruiting $m$ to any $m' > m + 1$). Further, the result states that under the test strategy the buyer will recruit a relatively small number of entrants if she realizes that the price she has to pay the winning incumbent is low, and she will be willing to recruit a larger number of entrants if she realizes the incumbents have high costs. This occurs because the expected benefit of recruiting an entrant supplier (namely, the reduction in the expected clearing price of the second auction for $Q-y$ units) increases as the clearing price of the test auction increases.

Although the result that the number of entrants to recruit is nondecreasing in the clearing price of the test auction may seem intuitive at first, it may not hold if our model's regularity assumption is violated. For example, consider the case where the buyer needs to source 1,000,000 units and the suppliers' cost distribution pdf is given by

$$f(x) = \begin{cases} 0.1 & \text{if} \quad x \in [8,9] \\ 0.9 & \text{if} \quad x \in [11,12] \\ 0 & \text{elsewhere.} \end{cases}$$

This cost distribution results in a uniformly-distributed cost on $[8,9]$ with 10 percent probability and a uniformly-distributed cost on $[11,12]$ with 90 percent probability. This represents the case where most suppliers are likely to have a relatively high cost, but a few may have a lower cost (e.g., because they have lower labor costs or have recently freed up capacity that they need to fill). Suppose the buyer has already sourced 300,000 units through an auction with the incumbent suppliers and she is deciding how many entrants to recruit before holding the second auction for the remaining units, and let the recruitment cost be $k(m) = 154{,}000 \cdot m$ — that is, the buyer's marginal cost of recruiting an entrant is constant. If the clearing price of the test auction is $x = 11$, the buyer will find it optimal to recruit one entrant prior to the second auction. However, if the clearing price of the test auction is $x = 11.1$, the buyer will find it optimal to recruit zero entrants — the number of entrants to recruit *decreases* when the clearing price of the test auction increases! When the clearing price is $x = 11$, the buyer is certain that the winning incumbent supplier has a cost in $[8, 9]$, and is willing to recruit an entrant because with probability 0.1 the entrant will also have a low cost, resulting in the buyer realizing significant savings in the second auction. However, when the clearing price is $x = 11.1$, the buyer is uncertain of whether the winning incumbent is in the $[8, 9]$ or $[11, 11.1]$ cost region (in fact, the winning incumbent has a cost in the higher region with probability 0.47). As a result, the buyer does not find it optimal to recruit entrant suppliers because the expected unit cost savings are less than the associated recruitment cost.

This example serves to point out that although it is intuitive that the number of entrants to recruit should increase in the clearing price of the test auction, this is not a foregone conclusion. What Proposition II.1 shows, however, is that $m_T^*$ increases in $x$ provided that we have regularity, namely $x + \frac{F(x)}{f(x)}$ increases in $x$. Note that the regularity condition is satisfied by many distributions such as the uniform, normal, and Pareto distributions and is also common in the auction literature, and we will use regularity in the sequel.

We finally note that it is never optimal for the buyer to use the no-test strategy and recruit $m_N^* = 0$ entrant suppliers. Such a policy is weakly dominated by using the test strategy: Instead of choosing to not recruit additional suppliers prior to procuring the entire batch of $Q$ units, the buyer could use the test strategy and do no worse in expectation. This indicates that buyers who just auction off their entire desired quantity without recruiting new suppliers (or running a test auction) are following a suboptimal policy. Thus, buyers who typically use only existing incumbent suppliers for new components without testing their prices first or recruiting entrants may have an opportunity to lower costs.

### 2.3.2 Test and No-Test Strategies with a Reserve Price

In the test strategy, the buyer opens the second auction's bidding at $X_{2:n}$, the clearing price of the test auction. The logic is simple: Since competition among incumbents already pushed the per-unit price to $X_{2:n}$ in the initial auction, the buyer knows she need not pay more than $X_{2:n}$ per unit in the second auction when she includes additional bidders (entrants). In this section we will allow for the possibility that the buyer might also use a reserve price in the test auction itself.

A test auction reserve price helps the buyer avoid paying a high cost in the test auction. But when the buyer sets a reserve price in the test auction, she must consider the possibility that this reserve price might not be met and thus the buyer might not transact with the suppliers in the auction. In practice, many buyers we have dealt with need to procure items that they are *not* capable of producing themselves. The buyer relies on suppliers for production. Although the auction literature commonly uses the notion of an "outside option cost" (needed when setting a reserve price), such a cost typically is assumed to be exogenous; for instance, the cost of forgoing the contract. However, would the buyer forgo the contract if the reserve price is not met? In reality, if the reserve price is not met and the buyer has sufficient time to recruit new entrants, a buyer could re-run the auction with a new set of suppliers.

This is what we capture in our model, as explained below. To our knowledge, this is the first paper to inform this decision by endogenizing the cost of recruiting new suppliers and re-running an auction.

If the buyer sets a reserve price $r_1$ for the test auction, one of three outcomes occur: (i) multiple incumbents bid at or below the reserve price and the ending price of the auction is set according to the second-lowest bid; (ii) exactly one incumbent bids at or below the reserve price and the ending price of the auction is set at the reserve price, or; (iii) no incumbent bids at or below the reserve price and there is no transaction. Following the test auction, the buyer decides how many entrant suppliers to recruit. To enforce the inherent threat of the reserve price, we assume the buyer discards any incumbent not meeting the reserve price. This means that under case (iii), the buyer removes all the incumbent suppliers from her supplier pool, and to satisfy her demand she recruits new entrants and then procures all the units from them in the second auction.

It is a weakly optimal strategy for the buyer to use a reserve price, since she can always set the reserve equal to the upper bound of the suppliers' unit cost, $b$. Of course, in the test auction she might set it below this level, knowing that she can recruit entrant suppliers for a second auction if the reserve is not met by an incumbent. That is, despite the fact that the buyer needs the units and must eventually transact with a supplier, she can take a risk and set a low reserve price in the test auction. If the test auction clears, its clearing price, $\min\{r_1, X_{(2:n)}\}$, acts as a de facto reserve price for the second auction as this price serves as the opening bid in the second auction (and the buyer also has the option to award the remaining $Q - y$ units to the lowest-bidding incumbent at this price). The buyer cannot use a lower reserve price in the second auction because the buyer does not have time to perform a second recruitment round if zero suppliers meet the reserve. For the same reason, if the test auction does not clear (zero incumbents meet the reserve $r_1$), the buyer sets the second auction's opening bid (reserve price) to $b$.

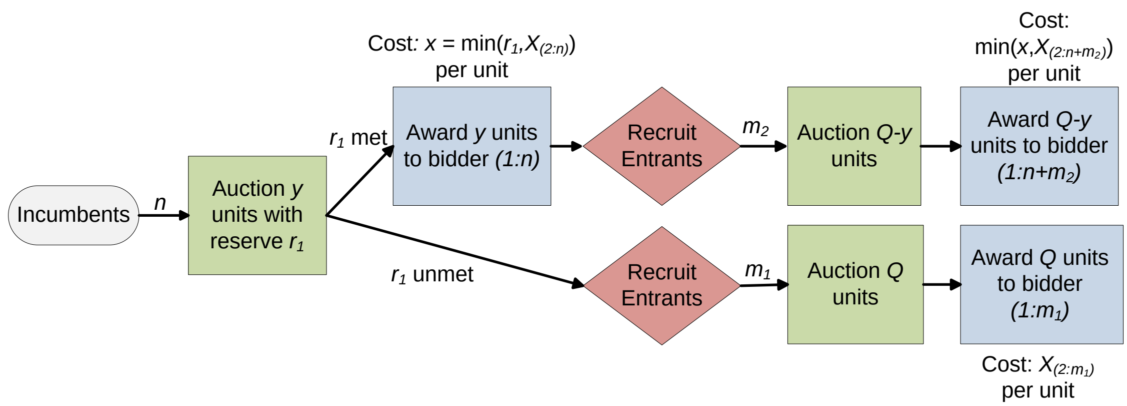



Figure 2.3: Timeline of the test with reserve price strategy.

Figure 2.3 depicts the timeline for the test with reserve price strategy. Under the test with reserve price strategy, the buyer first holds an auction with a reserve price ($r_1$) for the minimum order quantity ($y$ units) with only the $n$ incumbent suppliers. The buyer's optimal reserve price depends on her expected outside option cost – the cost which she expects to incur if zero incumbents meet the reserve. The buyer's outside option is purchasing the $Q$ units from the entrants, which in expectation costs her

$$C_1 \triangleq \min_{m_1 \geq 1} \left\{ \mathbb{E}[X_{(2:m_1)}]Q + k(m_1) \right\}, \tag{2.2}$$

where $m_1$ refers to the number of entrants that the buyer will recruit if the reserve $r_1$ is not met, and $X_{(2:1)} \triangleq b$, the upper bound of the suppliers' unit cost. When $m_1 = 1$, the buyer recruits a single entrant supplier and sets a reserve price equal to $b$ in order to award the $Q$-unit contract to the sole entrant at the upper bound of his unit cost distribution.

One can show that when the test auction starts at reserve price $r_1$, the incumbents still have a weakly dominant strategy of remaining in the test auction until either winning the auction or reaching their true cost. We now evaluate the buyer's test strategy when at least one incumbent bids down to the reserve price. If at least two incumbents meet the reserve, the buyer's per-unit payment for the first $y$ units is the second-lowest cost among the $n$ incumbent suppliers. If one incumbent meets the reserve, the buyer's payment for the first $y$ units is $r_1$ per unit. Hence, the expected cost of the first auction under the test strategy given that the reserve is met is $\mathbb{E}[\min\{X_{(2:n)}, r_1\}] \cdot y$. For convenience, we define $x$ as the realization of $\min\{X_{(2:n)}, r_1\}$, the clearing price of the test auction when the reserve is met. After holding the initial auction, the buyer must decide how many additional suppliers to recruit. The cost information revealed in the test auction (specifically, the value of $x$) allows the buyer to make a more informed decision than she would if she did not hold a test auction. The expected cost of the second auction (including recruitment costs) when $m_T$ additional suppliers are recruited is

$$\mathbb{E}[\min\{x, X_{(2:n+m_T)}\} | \min\{X_{(2:n)}, r_1\} = x](Q - y) + k(m_T). \tag{2.3}$$

In equation (2.3) the expectation is of the clearing price of the second auction, conditioned on the fact that the outcome of the test auction was clearing price $x$. Under the test with reserve price strategy, $m_T^*$ is the minimizer of (2.3). The buyer's total expected cost given that an incumbent meets the reserve price $r_1$ under the test strategy is the (expected) sum of the two auction costs and the recruitment costs:

$$C_2 \triangleq \mathbb{E}[\min\{X_{(2:n)}, r_1\}]y + \mathbb{E}\left[\mathbb{E}[\min\{x, X_{(2:n+m_T^*)}\} | \min\{X_{(2:n)}, r_1\} = x](Q - y) + k(m_T^*)\right].$$

We can now represent the buyer's total *ex ante* expected cost under the test strategy with reserve price $r_1$:

$$\Pr(X_{(1:n)} > r_1) \cdot C_1 + \Pr(X_{(1:n)} \leq r_1) \cdot C_2 \quad \text{(Buyer's expected cost under test).}$$

The first term addresses the buyer's cost when the test auction reserve price is not met, while the second term encompasses all cases where the reserve is met. Define

$$
\begin{aligned}
L(x) &\triangleq x \cdot y + \mathbb{E}[\min\{x, X_{(2:n+m_T^*)}\} | X_{(1:n)} \leq x \leq X_{(2:n)}] \cdot (Q - y) + k(m_T^*) \\
&= x \cdot y + \min_{m_T} \Big( \mathbb{E}[\min\{x, X_{(2:n+m_T)}\} | X_{(1:n)} \leq x \leq X_{(2:n)}] \cdot (Q - y) + k(m_T) \Big).
\end{aligned}
\tag{2.4}
$$

We now characterize the optimal reserve price, $r_1^*$, in terms of the buyer's expected outside option cost (equation (2.2)) and the buyer's total expected cost when the reserve price is met with clearing price $x$ (equation (2.4)). Specifically, the buyer-optimal reserve price $r_1^*$ for the test auction satisfies:

$$
r_1^* \triangleq \arg\min_{r_1 \in [a,b]} \left( \overline{F}(r_1)^n C_1 + nF(r_1)\overline{F}(r_1)^{n-1} L(r_1) + \int_a^{r_1} n(n-1) f(s) F(s) \overline{F}(s)^{n-2} L(s) ds \right)
\tag{2.5}
$$

where $\overline{F}(x) \triangleq (1 - F(x))$ is the complementary cumulative distribution function. In equation (2.5), the first term corresponds to the case where zero incumbents meet the reserve price, resulting in the buyer eliminating the incumbents from competition for the units and resorting to her outside option of recruiting new suppliers. The second term represents the case where a single incumbent meets reserve price $r_1^*$, resulting in a clearing price equal to the reserve. The final term covers cases where at least two incumbent suppliers meet the reserve price. We next show that when deciding how many entrants to recruit, the reserve price fits into the buyer's decision in a very straightforward way.

**Proposition II.2.** *If the reserve price is met and the clearing price is* $x = \min\{r_1^*, X_{(2:n)}\}$, *the buyer will recruit the same number of entrants as she would if* $x$ *were the clearing price of a test auction without a reserve price.*

We now address the use of a reserve price under the no-test strategy. Even though the reserve price helps protect the buyer from high incumbent costs in the test strategy, it may sometimes still be optimal to recruit entrant suppliers prior to holding the auction. Under the no-test strategy, the buyer performs recruitment *prior* to the auction. As a result, the buyer's optimal reserve price is the suppliers' per unit cost upper bound, $b$, because she would not be able to recruit additional suppliers if the reserve was unmet. Rather than using an aggressive reserve price rooted in the fallback option of recruiting additional entrants, in the no-test case the buyer has already gone ahead and recruited the additional entrants. In essence, instead of using a reserve price based on expectations of what these new suppliers' costs will be, the buyer simply includes these new suppliers in the auction. The upshot is that, although the buyer cannot use an interior reserve price in the no-test case, by proactively adding entrants to the supplier pool she lowers her unit costs for the *entire* $Q$-unit contract.

### 2.3.3 Comparison of the Strategies

To understand the trade-off between test and no-test, consider the following numerical example. Assume the suppliers' unit costs are uniformly distributed between \$5 and \$15, the buyer has 5 incumbent suppliers, needs to source 50,000 units, the minimum order quantity is 2,500 units, and the cost to recruit each entrant supplier is \$17,500 (e.g., this could be the cost of time spent gathering supplier lists, contacting suppliers and sifting through them for fit, working with engineering to explain the RFQ to them, training them on the auction platform, etc.). Under this scenario, if the buyer chooses the no-test strategy, she will find it optimal to recruit $m_N^* = 2$ entrant suppliers, and then hold one auction for all 50,000 units with the 7 suppliers. As a result, she will pay \$35,000 in recruitment costs and will expect to pay \$7.5 per unit, for a total expected cost of \$410,000.

If the buyer chooses the test strategy, she will first hold an auction for the minimum order quantity with the 5 incumbent suppliers and then decide how many entrant suppliers to recruit based on the clearing price of the first auction. Per Proposition II.1, the optimal number to recruit increases in the outcome of the test auction. In this example, she will recruit anywhere from 0 to 5 entrant suppliers, where the optimal number to recruit is illustrated by Figure 2.4.

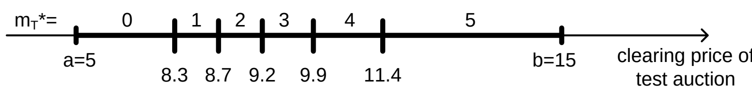



Figure 2.4: Optimal number of entrants to recruit given the clearing price of the test auction.

In this case, the test strategy results in an expected total cost (expected cost of the first auction, expected cost of the second auction, and expected recruitment costs) of \$397,013 — a net savings[1] of 8.1 percent. As a result, the buyer prefers the test strategy to the no-test strategy.

If the buyer can implement a reserve price in the test auction, the optimal reserve is $r_1^* = \$7.5$. If the reserve is met, Proposition II.2 states that the buyer will recruit the same number of entrants that she would recruit under the regular test strategy with the same clearing price (given by Figure 2.4); in this case the buyer would recruit zero additional suppliers and source all $Q$ units from the lowest cost incumbent. If the reserve is not met, the buyer would find it optimal to recruit 7 entrants and hold an auction for all $Q$ units among the entrants. In this case, the test with reserve price strategy results in an expected total cost of \$386,410 — a net savings of 14.7 percent over the no-test strategy.

Finally, since buyers in practice may be tempted to just auction a contract with-

[1]We define net savings as the percent savings after subtracting the baseline (minimum possible) cost — in this case, the baseline cost is $a \cdot Q = \$250{,}000$. The buyer will incur this baseline as part of her cost regardless of her strategy, and thus we do not consider it when comparing her options.

out running a test auction or recruiting additional suppliers, we consider the case where the buyer holds a single auction, only inviting the incumbents. In this case, implementing the test strategy without (with) a reserve price results in a net savings of 11.8 (18.2) percent over this suboptimal policy. Once again, in an environment where 2-3% savings can amount to millions of dollars a year, the advantages of a more sophisticated strategy as proposed in this paper can be significant.

The following comparative statics provide insights that are helpful for buyers wondering if a test auction approach is appropriate for their situation.

**Proposition II.3.** *(i) Holding all other parameters constant, the buyer prefers the test strategy without a reserve price over the no-test strategy if*

*(a) The minimum order quantity, $y$, is sufficiently small.*

*(b) The number of incumbents, $n$, is sufficiently large.*

*(c) The new supplier recruitment cost, $k(m)$, grows proportionately large enough (i.e., the recruitment cost is taken to be $a \cdot k(m)$ and $a \in \mathbb{R}^+$ is sufficiently large).*

*(d) The cost distribution variance factor $\alpha$ is sufficiently small, where $\tilde{f}(x) = f(\frac{x+\Delta}{\alpha})$ with $\Delta \in \mathbb{R}$ and $\alpha \in \mathbb{R}^+$.*

*(ii) Moreover, if the buyer prefers the test without a reserve price strategy to the no-test strategy, then the buyer prefers the test with a reserve price strategy to the no-test strategy.*

To understand part (a), note that a smaller $y$ makes the test auction more attractive because the risk with a test strategy is that an incumbent wins an order at a high price. However, as $y$ decreases, the amount risked becomes smaller. Similar intuition explains part (b): When the number of incumbents is large, there is more competition during the test auction stage and the buyer is less likely to pay a high price for the first $y$ units, increasing the attractiveness of the test auction.

Part (c) follows because when it is expensive to recruit suppliers, the buyer needs to be more judicious about how many entrants to recruit. Using a test auction helps her decide the exact number of entrants to recruit and avoids the risk of recruiting too many, which would be expensive when the function $k(m)$ grows proportionately larger. Part (d) appears counterintuitive at first sight. After all, one may think that price discovery is more beneficial when prices are more variable. The flip side of the coin is that when prices are less variable, the firm has a lower chance of paying too much for the first $y$ units in a test auction and the test auction is less risky. Finally, part (ii) of the proposition follows from the fact that allowing the buyer to use a reserve price never makes her worse off.

#### 2.3.4 Optimal Mechanism

In the previous subsection, we investigated when the buyer can benefit from implementing the test auction strategy versus the commonly-employed no-test strategy. Although we saw that employing test auctions can provide significant benefits, it would be interesting to see how well the test strategy performs compared to an optimal mechanism the buyer may use to source parts. We note that optimal mechanisms are often difficult to implement but serve as good bounds on the performance of more easily implementable approaches. To this end, we find the optimal mechanism for the buyer's procurement problem in order to investigate our test strategy's relative performance. The revelation principle is described in Krishna (2002) as follows: "Given a mechanism and an equilibrium for that mechanism, there exists a direct mechanism in which (i) it is an equilibrium for each [supplier] to report his or her value truthfully and (ii) the outcomes are the same as in the given equilibrium of the original mechanism." We can apply the revelation principle in our setting, where the equilibrium involves the suppliers' bidding strategy, the buyer's allocation and payment rules, *and the buyer's recruitment decision rule.* Thus, we restrict our attention to direct mechanisms, as formalized below.

For supplier $i$, we denote his reported cost as $s_i$ and his true cost as $x_i$, and we use $-i$ to represent $j$, $\forall j \neq i$. The purchase quantity from and payment to supplier $i$ are denoted by $Q_i(s_i, s_{-i})$ and $P_i(s_i, s_{-i})$, respectively. When supplier $i$ reports cost $s_i$ and all other suppliers report their cost truthfully, supplier $i$'s expected payment, quantity, and utility are, respectively, $p_i(s_i) = \mathbb{E}_{X_{-i}}[P_i(s_i, X_{-i})]$, $q_i(s_i) = \mathbb{E}_{X_{-i}}[Q_i(s_i, X_{-i})]$, and $u_i(s_i) = p_i(s_i) - x_i q_i(s_i)$. We refer to the vector of incumbents' costs as $x^I$, and let $m_T(x^I)$ denote the number of entrants the buyer recruits based on the incumbents' costs. Similarly, we let $x^E$ denote the vector of the recruited entrant's costs, and let $x \triangleq [x^I, x^E]$.

The buyer's mechanism design problem is

$$\min_{Q_i(x), P_i(x), m_T(x^I)} \quad \mathbb{E}\Big[k(m_T(X^I)) + \sum_{i=1}^{n+m_T(X^I)} p_i(X_i)\Big] \tag{2.6}$$

$$\text{s.t.} \quad u_i(x_i) \geq 0 \qquad \forall x_i, \forall i \tag{2.7}$$

$$u_i(x_i) \geq u_i(s_i) \qquad \forall s_i \neq x_i, \forall x_i, \forall i \tag{2.8}$$

$$\sum_{i=1}^{n+m_T(x^I)} Q_i(x_i, x_{-i}) = Q \qquad \forall x \tag{2.9}$$

$$Q_i(x_i, x_{-i}) \in \{0, y, y+1, \ldots, Q\} \quad \forall x, \forall i \tag{2.10}$$

The objective function states that the buyer minimizes her expected total cost (recruitment costs plus payments to suppliers) by choosing the quantity allocation rule, payment rule, and the number of recruited entrants, $m_T(x^I)$. Equation (2.7) is the standard individual rationality constraint, while equation (2.8) is the incentive compatibility constraint. Equation (2.9) states that the desired $Q$ units has to be procured, while (2.10) addresses the minimum order quantity, $y$, consistent with our model described in §2.2. The quantity allocation, payment, and recruitment rules that solve this constrained cost minimization problem will serve as a lower bound on the expected cost the buyer could achieve regardless of sourcing mechanism — whether it be the test strategy, no-test strategy, or any other sourcing mechanism (e.g., negotiation, first-price sealed-bid auction, Dutch auction, etc.). Let $\psi(x_i) = x_i + \frac{F(x_i)}{f(x_i)}$ denote the virtual cost function, where $\psi(\cdot)$ is increasing because of the regularity assumption.

**Proposition II.4.** *The following constitutes an optimal mechanism: Based on the incumbent suppliers' reported cost vector $x^I$, the number of entrants recruited by the buyer is*

$$m^*_T(x^I) = \underset{m_T(x^I)\in\mathbb{N}}{\arg\min}\left\{ k(m_T(x^I)) + \mathbb{E}[\psi(X_{(1:n+m_T(x^I))})|x^I_{(1:n)})] \cdot Q \right\} \tag{2.11}$$

*where $m^*_T$ is nondecreasing in $x^I_{(1:n)}$ and constant in $x^I_{(2:n)}, x^I_{(3:n)}, \ldots, x^I_{(n:n)}$. Define*

$$\tilde{x}^I \triangleq \begin{cases} [t_i, x^I_{(2:n)}, x^I_{(3:n)}, \ldots, x^I_{(n:n)}] & \text{if} \quad x_{(1:n+m^*_T(x^I))} = x^I_{(1:n)} \\ x^I & \text{otherwise.} \end{cases}$$

*Let $i$ be the lowest-cost supplier, i.e., $x_i = x_{(1:n+m*T(x^I))}$. The buyer pays $i$*

$$P^*(x) = x_{(1:n+m^*_T(x^I))} \cdot Q + \int_{x_{(1:n+m^*_T(x^I))}}^{x_{(2:n+m^*_T(x^I))}} (1 - F(t_i))^{(m^*_T(\tilde{x}^I) - m^*_T(x^I))} \cdot Q dt_i \tag{2.12}$$

*to supply the $Q$ units while the remaining suppliers are not awarded any units and are paid zero.*

Under this mechanism, the buyer views the incumbents' vector of reported costs, $x^I$, and recruits $m^*_T(x^I)$ entrants based on these reports. After the $m^*_T(x^I)$ entrants report their costs, the buyer awards the $Q$-unit contract to the supplier with the lowest report and pays him $P^*(x)$. The first term of (2.12) is the winning supplier's true cost, while the second term represents a markup that rewards the supplier for truthfully revealing his cost. If the winning supplier is an entrant supplier, we note that $\tilde{x}^I = x^I$ and the markup is equal to the difference between the second-lowest report and the winning supplier's report. Thus, in the case where an entrant is awarded the contract, $P^*(x) = x_{(2:n+m_T^*(x^I))} \cdot Q$ and the winning entrant supplier is paid the second-lowest reported cost.

We now address the markup when the winning supplier is an incumbent. The markup paid to a winning incumbent supplier represents the amount by which the supplier could have inflated his reported cost and still won the contract. The important point is that a winning incumbent supplier's reported cost also influences the buyer's recruitment decision. Hence, the markup of an incumbent supplier who eventually wins the contract must account for the increased competition (i.e., $m_T^*(\tilde{x}^I) - m_T^*(x^I)$ additional entrants) associated with an inflated reported cost.

Although the optimal mechanism described in Proposition II.4 results in the minimum expected cost for the buyer, the buyer may still be unable to use such a mechanism in practice. The described mechanism requires the incumbent suppliers to reveal their true cost *before* the buyer recruits suppliers to compete for the units up for bid. Revealing such information prior to the recruitment round will not result in a contract (even for the minimum order quantity) for the incumbents — it will only help the buyer make a more accurate decision on how many entrants to recruit. A buyer may find it difficult to convince a supplier to reveal his cost information just so the buyer can decide how many suppliers to recruit to compete against him. Although the test strategy analyzed in §2.3.1–2.3.3 allows the buyer to gather quotes from the incumbents, the guaranteed award of a minimum of $y$ units to the winning incumbent supplier (given he meets the reserve price, if applicable) provides an incentive for the incumbents to reveal such information — it is the minimum quantity required to induce suppliers to bid. There is no such offer under the optimal mechanism. Further, we note that in the test strategy bidders have to beat their competitors' pricing but do not have to reveal their true cost to win; under this mechanism, the lowest-cost supplier still has to reveal his cost.

Regardless of whether the buyer would be able to implement the optimal mechanism in practice, the optimal mechanism can be used as a theoretical benchmark to quantify the relative performance of the test and no-test strategies; the "optimality gap" between the optimal mechanism and the test and no-test strategies can help the buyer gauge whether the cost and effort of attempting to implement more complex mechanisms than the test and no-test strategies are worth the savings.

#### 2.3.5 Comparison of the Optimal Mechanism with Test and No-Test Strategies

We can now compare the buyer's expected cost under the optimal mechanism to her costs when employing the test and no-test strategies. We calculated the test and no-test strategies' performance relative to the optimal mechanism in a wide range of situations by generating 81 problem instances. We chose a low, medium, and high value for the recruitment cost, number of incumbents, width of the suppliers' cost distribution, and minimum order quantity that needs to be offered to suppliers in the test auction to induce them to participate, where the medium value corresponded to the value from the example in §2.3.3. Specifically, the parameters studied included $k(m) \in \{12500m, 17500m, 22500m\}$, $n \in \{2, 5, 8\}$, $\mathrm{U}[a, b] \in \{\mathrm{U}[2.5,17.5], \mathrm{U}[5,15], \mathrm{U}[7.5,12.5]\}$, and $y \in \{500, 2500, 4500\}$.

We calculated the optimal mechanism's expected cost as follows: For the given problem parameters, costs are randomly generated according to the distribution $F$ for the incumbent suppliers. Given these costs, the optimal number of entrants are recruited and their costs are revealed; finally, the buyer pays the amount given by (2.12). Because this calculation depends on the randomly-generated costs of the incumbents, we run this simulation for 1,000,000 replications for that problem instance and calculate the average. We call this average the optimal mechanism's expected cost for the given problem instance.

For these 81 scenarios, the optimal mechanism provides a relatively substantial average net savings of 8.4 percent over the minimum expected cost of the no-test and test (without reserve price) strategies, while it only provides an average net savings of 1.9 percent over the minimum of the no-test and test with reserve price strategies. In these calculations, we compare the optimal mechanism to the minimum of the no-test and test strategies because the buyer will decide *a priori* which strategy to use based on the problem instance's parameters. Further, in these 81 scenarios the test with reserve price strategy provides an average net savings of 10.2 percent over the no-test strategy. Thus, when the buyer can use a reserve price, the intuitive and easily-implementable test strategy provides the buyer with significant savings and near-optimal results. The implications of this observation are important to reiterate: The buyer can use an easily-implementable strategy with an auction mechanism very familiar to practitioners that will provide average net savings of over 10 percent compared to the commonly-used no-test strategy, and furthermore this easily-implementable strategy only performs a mere 2 percent worse than the optimal mechanism. For these reasons, we believe that the test with reserve price strategy is a powerful sourcing mechanism for buyers.

Finally, we are interested in further exploring when the test with reserve price strategy performs well and when it performs poorly compared to the optimal mechanism. To this end, we vary the problem parameters beyond the aforementioned 81 instances. Once again, we use the example from §2.3.3 as a base case, where the default parameter values were $F \sim$ U[\$5, \$15], $Q$ = 50,000, $y$ = 2,500, $k(m)$ = \$17,500$m$, and $n = 5$.

First, the (constant) marginal cost of recruiting an entrant was varied from \$2,000 to \$160,000: Figure 2.5 shows that the net savings of the optimal mechanism over the minimum of the no-test and test with reserve price strategies is increasing and then decreasing in the recruitment cost. For extremely low recruitment costs, the buyer will use the no-test strategy and recruit a large number of entrants prior to holding an auction; likewise, under the optimal mechanism the buyer will (most likely) recruit many entrants after viewing the incumbents' costs. However, as the recruitment cost increases the value of viewing the incumbents' costs increases until a certain point, after which the value decreases because the buyer will be less inclined to recruit entrants due to the recruitment cost. We note that the slight "noise" in the graph (and subsequent graphs) is due to the numerical calculation via simulation of the optimal mechanism's expected cost, as described above.

Second, the number of incumbent suppliers was varied from 2 to 30. Figure 2.6 shows that the net savings of the optimal mechanism increases and then decreases in the number of incumbents. Using similar intuition from the recruitment cost case, for very small and large $n$, the buyer's recruitment decision hinges less on the incumbents' cost information; the buyer will be more inclined to recruit a lot (in the case of very small $n$) or few (in the case of large $n$) entrants regardless of the cost information, so the value of the optimal mechanism with respect to the test and no-test strategies decreases.

The width of the suppliers' cost distribution (originally U[\$5,\$15]) was varied while holding the midpoint of the cost distribution constant at \$10 – the widest cost

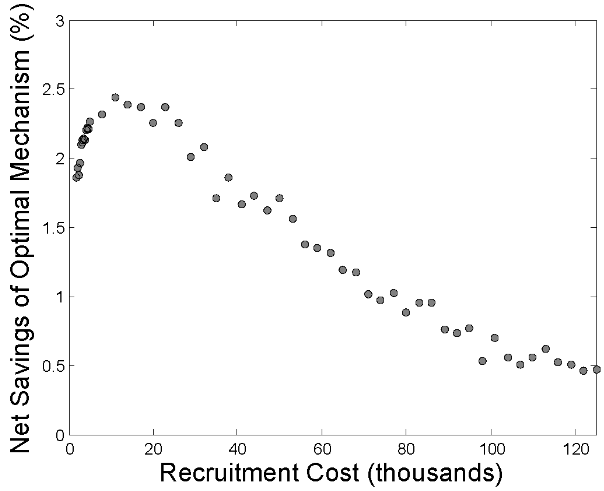



Figure 2.5: Buyer's net savings as a function of the constant marginal recruitment cost.

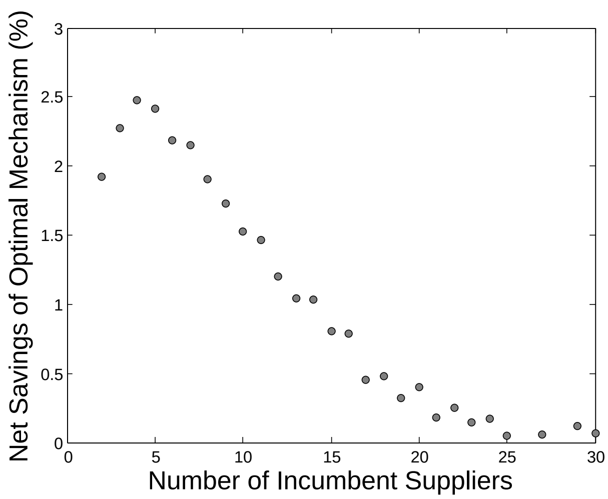



Figure 2.6: Buyer's net savings as a function of the number of incumbent suppliers.

distribution studied was U[\$0,\$20] and the narrowest was U[\$9.4,\$10.6]. Figure 2.7 shows that the optimal mechanism's net savings grow at a decreasing rate as the width of the suppliers' cost distribution increases; as the variability of the incumbents' costs increase, the value of being able to view the incumbents' cost information without having to allocate any quantity to incumbents increases due to the increased uncertainty in cost.

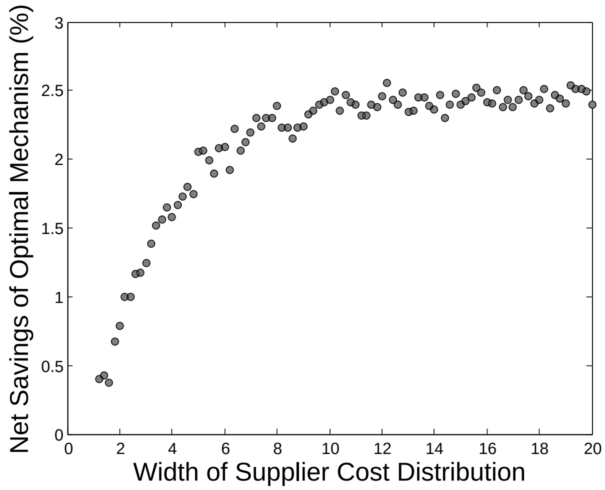



Figure 2.7: Buyer's net savings as a function of the cost distribution's width.

## 2.4 Extensions

### 2.4.1 Other Auction Mechanisms

We studied the open-bid descending-price auction format due to its prevalence in industry, the intuitive nature of its mechanics, and the attractive simplicity of the suppliers' optimal bidding strategy (as proved in Proposition II.1). However, there are a variety of different auction formats that could be used in lieu of the open-bid descending-price auction.

Another auction format that is studied in the literature and also used in practice is the first-price sealed-bid auction. Unfortunately this auction format is generally intractable analytically for our test-strategy setting due to bidder asymmetry resultant from bidders' belief updating: Suppose an incumbent supplier wins the test auction at a clearing price of $x$. The buyer then decides how many entrant suppliers to recruit (say $m^*$) to compete against this winning incumbent supplier in the second auction for the remaining $Q - y$ units. The second auction will then be an auction with ex ante asymmetric bidders. Namely, each supplier is aware that at least one of the other suppliers has a different cost distribution: Given the number of entrants that the buyer recruits and the opening price (i.e. the reserve price) of the second auction, the entrant suppliers can update their belief regarding the incumbent's cost.

In general, an equilibrium bidding strategy cannot be found in such asymmetric first-price sealed-bid auctions: Hartline et al. (2014) note that when "the agents' values for the item are non-identically distributed, analytically solving for equilibrium is notoriously difficult" while many others have confirmed the same (see e.g., Lebrun (1991), Maskin and Riley (2000b)). There are a variety of papers that examine the two-bidder case and find equilibrium bidding strategies for the two asymmetric bidders (e.g., Mares and Swinkels (2014), Plum (1992), Lebrun (1991), Maskin and Riley (2000a)). Of course, in our case there may be more than two bidders. Lebrun (1999) finds positive results for the $n$ bidder case where suppliers' cost distributions have supports equal to the same interval. This is not the case in our setting, as the winning incumbent supplier's cost distribution will have support on $[a, x]$ while the entrant suppliers' cost distribution will have support on $[a, b]$. Finally, the case closest to our model — where all bidders except one have the same valuation probability measure — was numerically examined by Marshall et al. (1994). However, to our knowledge no analytical results exist for this case. The same applies for the reverse Dutch auction (whereby a price clock rises until a bidder ends the auction by accepting the contract), as this format is strategically equivalent to a first-price sealed-bid auction. The reverse Dutch auction is the other auction format the authors have seen used in practice.

Regardless of these intractability issues, for these other auction formats used in practice the following result generalizes Proposition II.3, which described the buyer's preference between the test and no-test strategies. To account for the role of belief updating during the test strategy, we will assume the buyer has discretion over whether to announce the number of entrants she recruits for the second auction, whether to announce an opening bid for the second auction, etc., as such announcements reveal information that the entrants could use when updating their beliefs.

**Proposition II.5.** *If the buyer uses sealed-bid first-price or reverse Dutch auctions instead of open-bid descending-price auctions, then Proposition II.3 goes through as before.*

Finally, we note that the relatively small optimality gap (1.9% net savings in our numerical study) between the second-price open-bid auction formats and the optimal mechanism studied in §2.3 should reassure practitioners that the use of other contracting mechanisms would provide at most minimal savings over our proposed strategies.

### 2.4.2 Test Auction Strategy with Non-Independent Costs

We have emphasized the buyer's opportunities for cost savings by using a test auction strategy that allows the buyer to gain more information regarding incumbent suppliers' costs before making a recruitment decision. The preceding analysis assumed a private values framework, where suppliers' costs are independent and identically distributed according to cumulative distribution $F$ with probability distribution $f$. Further, the cost distribution $F$ is known to all suppliers and the buyer. Thus, in our model the incumbent cost information gathered in the test auction does not influence the buyer's belief regarding the entrant suppliers' costs. However, there may be certain situations where this is not the case; the buyer may be able to update her belief on the entrant suppliers' cost distribution based on the incumbent suppliers' bid-down-to levels in the first test auction. For example, all suppliers may share similar costs for things like commodity input prices or shipping/freight costs.

Thus, suppose the buyer has an initial belief that the suppliers' cost distribution is $F$, and to update her belief after the test auction, the buyer refines her belief to the distribution $F(\cdot|b_1, b_2, \ldots, b_{n-1})$ with density $f(\cdot|b_1, b_2, \ldots, b_{n-1})$, where $b_i$ represents the $i^{th}$ drop-out bid (i.e., the data the buyer observes) in the test auction.

In our original model we showed that incumbents had a dominant strategy of remaining in an auction until either winning or reaching their true cost. This bidding strategy was the bidders' best response to the buyer's recruitment strategy, where the number of recruited entrants increases in the test auction's clearing price. However, in the setting where the buyer updates her belief on the underlying supplier cost distribution, things become more complex. In such a case, even if the incumbents bid down to their true cost, the buyer's recruiting strategy need not have the same property as before. In fact, the number of entrants the buyer recruits could conceivably be decreasing in the test auction clearing price. For example, imagine a case where the clearing price of the auction is high, but the buyer's updated belief confirms that an entrant supplier will be unlikely to have lower costs than the clearing price of the test auction. Even though the clearing price is high, the buyer will recruit fewer entrant suppliers than she might under an alternative scenario where the clearing price is low but the buyer anticipates that entrant suppliers will provide a cost savings. In the context of this example, one can see how incumbent suppliers may want to alter their bidding strategy to influence the buyer's recruitment decision. Therefore, to ensure that incumbents still find it optimal to bid aggressively in the test auction, the buyer needs to add bigger "teeth" to her auction policy: She promises to only allow the test auction winner to participate in the second auction.[2] Under this more stringent policy, the incumbent bidders can be shown to have a

[2] By contrast, despite being mild, this assumption was not required in §2.3.1–2.3.3 so we did not impose it there.

dominant strategy of remaining in the auction until either winning or reaching their true cost. We also note that, unlike before, the buyer's recruitment strategy need not depend on just the test auction's clearing price; indeed, one can easily see that the buyer's recruitment policy depends on her updated belief about the underlying cost distribution, $F(\cdot|b_1, b_2, \ldots, b_{n-1})$, which would in general depend on the drop-out bids of the incumbents that the buyer observes in the test auction. The following result formalizes these insights.

**Proposition II.6.** *Suppose that under the test strategy the buyer only allows incumbent suppliers awarded units in the test auction to compete with entrant suppliers in the second auction. Then, when the buyer can update her belief about the suppliers' cost distribution:*

*(i) Suppliers in an auction will remain in it until either the price reaches their true cost or they win the auction, whichever happens first.*

*(ii) Under the test strategy, the optimal number of suppliers to recruit, $m_T^*$, is a function of the drop-out bids of the $n-1$ incumbent suppliers who do not win the first test auction, which is equal to their per-unit costs: $X_{(2:n)}, X_{(3:n)}, \ldots, X_{(n:n)}$.*

Unlike Proposition II.1, which stated that for our original model that the number of entrants the buyer recruits is solely dependent on the clearing price of the first auction, we note that here the drop-out bids of the $n-1$ incumbent suppliers who do not win the test auction influence $m_T^*$ under the case of information updating. This evidences an additional benefit of using a test auction when the buyer updates her belief about the cost distribution: In addition to refining her knowledge of the *relative* cost differences of the incumbents, the buyer learns about the underlying cost distribution of the suppliers. But as before, the primary benefit of the test auction still stems from reducing the buyer's exposure to relatively high-cost incumbent suppliers.

The reserve price result from §2.3.2 no longer applies when the buyer updates her belief of the suppliers' cost distribution. Although Proposition II.2 states that the buyer recruits the same number of entrants regardless of the test auction clearing price's origin, under the case of cost distribution updating the buyer may make different recruitment decisions based on whether an incumbent supplier or the pre-announced reserve price determines the clearing price of the test auction. The list of the drop-out bids of the incumbent suppliers will differ between the two cases, allowing different updates to the buyer's beliefs; obviously, if the buyer has different beliefs under the two cases, she may also recruit a different number of entrants.

In spite of these interesting differences, we conclude by noting that the comparative statics insights from Proposition II.3 continue to hold under the case of information updating.

**Proposition II.7.** *When the buyer updates her beliefs about the suppliers' cost distribution given the drop-out bids from the test auction according to $F(\cdot|b_1, b_2, \ldots, b_{n-1})$ and only allows the incumbent supplier (if any) who is awarded units in the test auction to compete with entrant suppliers in the second auctions, then Proposition II.3 holds as before, with the following change: In part (i)(d), the buyer's ex ante and updated beliefs are given by $\tilde{f}(x) = f(\frac{x+\Delta}{\alpha})$ and $\tilde{f}(x|b_1, b_2, \ldots, b_{n-1}) = f(\frac{x+\Delta}{\alpha}|\frac{b_1+\Delta}{\alpha}, \frac{b_2+\Delta}{\alpha}, \ldots, \frac{b_{n-1}+\Delta}{\alpha})$ with $\Delta \in \mathbb{R}$ and $\alpha \in \mathbb{R}^+$, respectively.*

## 2.5 Conclusions

In this chapter we have addressed a fundamental question in sourcing that has received surprisingly little attention in the literature to date: How does a buyer who already has a set of suppliers she has worked with in the past balance the cost of recruiting even more suppliers against the (uncertain) savings that she would accrue by doing so? The key question we address is whether it is better for the buyer to immediately recruit more suppliers and auction off the contract or first run a test auction to gain a better understanding of the incumbent suppliers' costs for the new contract and use that information to assess how many more suppliers to recruit. It is natural for buyers to want to test the market by contracting out a portion of their total purchase quantity. Therefore, we believe our paper makes a practical contribution to the sourcing literature by providing a framework for characterizing buyers' test auction strategies. Further, we show that the test strategy is especially beneficial for the buyer as the minimum order quantity or the cost distribution's variance decreases, or the recruitment cost or number of incumbents increases. We show that these results apply to a variety of auction formats (e.g., sealed-bid first-price and Dutch auctions) even though such auctions result in bidding strategies that are much more difficult to analyze and thus provide additional challenges for implementation.

Additionally, we analyzed how the buyer can incorporate a reserve price into her procurement strategy. We provide a natural way to model the outside option through the buyer's ability to recruit new suppliers. Our analysis of the reserve price is of practical importance because reserve prices are ubiquitous in sourcing, and unlike past papers in the literature, our paper endogenizes the reserve price based on the actual costs that the firm would have to incur to recruit new bidders if its reserve is not met. Although the auction literature commonly uses the notion of an outside option cost (needed when setting a reserve price), such a cost is typically assumed to be exogenous. For instance, the outside option cost associated with a procurement auction's reserve price is often taken to be some exogenous value that is described as the cost of in-house production. In contrast, we endogenize this cost — namely, the cost of recruiting new suppliers and running a new auction. This is extremely relevant in many real-life situations. In practice, many buyers we have dealt with (including the buyer described in the Introduction) need to procure items that they are *not* capable of producing themselves. The buyer relies on outside suppliers for production, a fact which she must carefully consider when setting, say, a reserve price. To our knowledge, this is the first paper to inform this decision by endogenizing the cost of recruiting new suppliers and re-running an auction.

Finally, our numerical results indicate that the test with reserve price strategy performs nearly as well as the optimal mechanism under a wide variety of scenarios. Further, although the optimal mechanism can be extremely difficult to implement in practice, the test strategy is an easily implementable strategy for buyers. Given that costly new supplier recruitment is a key aspect of global supply chain management, we believe our work is applicable in a wide variety of industrial settings, and can spur future studies on using market test processes (such as test auctions) to help better manage recruitment costs.

## 2.6 Proofs for Chapter II

### 2.6.1 Proof of Proposition II.1

**No-test.** The dominant bidding strategy result follows from Krishna (2002). Since the marginal cost of recruiting a supplier is nondecreasing (as $k(m)$ is increasing convex), to show convexity of total cost in $m_N$ it suffices to show that the expected per-unit purchase price is decreasing discrete convex in the number of recruited suppliers. This in turn is implied by regularity; to see this, take the auction's expected per-unit clearing price, $a+\int_a^b(1-F(s))^{n+m_N}ds+\int_a^b(n+m_N)F(s)(1-F(s))^{n+m_N-1}ds$, and integrate the last term by parts and then differentiate with respect to $m_N$ twice.

**Test.** We first characterize the buyer's "best response" $m_T^*$ under the supposition that suppliers remain in an auction until either winning or reaching their true cost. We then show that given the buyer's strategy the supposed supplier strategy indeed constitutes an equilibrium.

Let the outcome of the test auction be denoted by $X_{(2:n)} = x$. For the second auction, let $\mathbb{E}[\text{MB}_m(x)]$ denote the expected per-unit purchasing price when $m-1$ entrants are recruited minus the same when $m$ entrants are recruited — in other words, the expected per-unit marginal decrease in purchase price resultant from recruiting the $m^{\text{th}}$ entrant supplier. Let $\hat{\hat{X}}$ represent the random variable following distribution $\hat{\hat{F}}(y) = F(y)/F(x)$ for $y \in [a, x]$. We can write

$$\mathbb{E}[\text{MB}_m(x)] = F(x)\left[\sum_{i=0}^{m-1}\binom{m-1}{i}F(x)^i(1-F(x))^{m-1-i}[\mathbb{E}[\hat{\hat{X}}_{(2:i+1)}] - \mathbb{E}[\hat{\hat{X}}_{(2:i+2)}]]\right],$$

where $\mathbb{E}[\hat{\hat{X}}_{(2:1)}] \triangleq x$. The leading $F(x)$ reflects the fact that the $m^{\text{th}}$ entrant has an effect only if its cost lies below $x$, and the summation over $i$ corresponds to $i$ of the other $m-1$ entrants having a cost below $x$ as well. Similarly, we can write

$$\begin{aligned}\mathbb{E}[\text{MB}_{m+1}(x)] =& (1-F(x))\mathbb{E}[\text{MB}_m(x)] \\ &+ \big(F(x)\big)^2\left[\sum_{i=0}^{m-1}\binom{m-1}{i}F(x)^i(1-F(x))^{m-1-i}[\mathbb{E}[\hat{\hat{X}}_{(2:i+2)}] - \mathbb{E}[\hat{\hat{X}}_{(2:i+3)}]]\right] \\ \le& \mathbb{E}[\text{MB}_m(x)]\end{aligned}$$

where the inequality follows since $\mathbb{E}[\hat{\hat{X}}_{(2:i+1)}] - \mathbb{E}[\hat{\hat{X}}_{(2:i+2)}] \ge \mathbb{E}[\hat{\hat{X}}_{(2:i+2)}] - \mathbb{E}[\hat{\hat{X}}_{(2:i+3)}]$ by regularity of $\hat{\hat{F}}$ (which follows from regularity of $F$). Since the supplier recruitment cost is convex, the buyer's expected total (recruitment plus second-auction purchase) cost is discrete convex in $m$.

To prove that the buyer's optimal number of entrants to recruit is nondecreasing in the clearing price, we first establish the following lemma.

**Lemma II.8.** *The expected marginal benefit of adding the $m^{th}$ supplier is nondecreasing in $x$.*

*Proof of Lemma II.8* This can be seen using a sample path argument: Suppose there are $m-1$ entrants. Order the cost of the incumbent who won the test auction and the $m-1$ realizations of entrant costs such that $x_1 \leq x_2 \leq \cdots \leq x_m$. Now consider adding an $m^{\text{th}}$ entrant with cost realization $z$. We will show that the buyer's marginal benefit does not decrease in the test auction clearing price $x$ under any sample path. We know that $x_1 \leq x$ since the incumbent's cost is at most $x$. There are two cases to consider.

**Case 1.** $x_1 \leq x \leq x_2$ or $m = 1$. The buyer's marginal benefit of recruiting the $m^{\text{th}}$ entrant is

$$x - x_1 \quad \text{if} \quad z \leq x_1 \leq x, \tag{2.13}$$

$$x - z \quad \text{if} \quad x_1 \leq z \leq x, \quad \text{and} \tag{2.14}$$

$$0 \quad \text{if} \quad x_1 \leq x \leq z. \tag{2.15}$$

Now consider the case where the test auction clearing price is $x' > x$. Under this sample path, (2.13) becomes $\min\{x', x_2\} - x_1$, (2.14) becomes $\min\{x', x_2\} - z$ (where if $m = 1$ we take $x_2 = \infty$), and (2.15) becomes a nonnegative quantity (as the second auction's clearing price cannot increase when the $m^{\text{th}}$ entrant is added). Thus, the buyer's marginal benefit of adding the $m^{\text{th}}$ entrant when the clearing price is $x'$ is greater than or equal to her marginal benefit when the clearing price is $x$ under all sample paths where $x_1 \leq x \leq x_2$.

**Case 2.** $x_2 \leq x$. The buyer's marginal benefit of recruiting the $m^{\text{th}}$ entrant is $x_2 - x_1$ if $z \leq x_1 \leq x_2$; $x_2 - z$ if $x_1 \leq z \leq x_2$; and 0 if $x_1 \leq x_2 \leq z$. When the test auction clearing price is $x' > x$, the buyer's marginal benefit is unchanged under all three cases.

In conclusion, for all sample paths, the buyer's marginal benefit of adding the $m^{\text{th}}$ entrant is nondecreasing in the clearing price of the test auction. As this holds for any sample path, it must hold in expectation. $\square$

This lemma implies that $m_T^*$ is nondecreasing in $x$. To see this, let $m_T^*$ be the buyer's optimal number of entrants to recruit given clearing price $x$. We will show that the buyer prefers to recruit $m_T^*$ entrants over $\underline{m_T} < m_T^*$ entrants for any $x' > x$. Let $\mathbb{E}[\mathrm{TB}_m(x)] \triangleq \sum_{i=1}^{m} \mathbb{E}[\mathrm{MB}_i(x)]$ denote the buyer's total expected benefit of recruiting $m$ entrants given clearing price $x$. The optimality of $m_T^*$ at clearing price $x$ implies

$$\begin{aligned}
&\mathbb{E}[\mathrm{TB}_{m_T^*}(x)] - k(m_T^*) > \mathbb{E}[\mathrm{TB}_{\underline{m_T}}(x)] - k(\underline{m_T}) \\
\implies &\sum_{i=1}^{m_T^*} \mathbb{E}[\mathrm{MB}_i(x)] - k(m_T^*) > \sum_{i=1}^{\underline{m_T}} \mathbb{E}[\mathrm{MB}_i(x)] - k(\underline{m_T}) \\
\implies &\sum_{i=\underline{m_T}+1}^{m_T^*} \mathbb{E}[\mathrm{MB}_i(x)] - (k(m_T^*) - k(\underline{m_T})) > 0.
\end{aligned}$$

Finally, Lemma II.8 implies $\sum_{i=\underline{m_T}+1}^{m_T^*} \mathbb{E}[\mathrm{MB}_i(x')] \geq \sum_{i=\underline{m_T}+1}^{m_T^*} \mathbb{E}[\mathrm{MB}_i(x)]$ so

$$\begin{aligned}
&\sum_{i=\underline{m_T}+1}^{m_T^*} \mathbb{E}[\mathrm{MB}_i(x')] - (k(m_T^*) - k(\underline{m_T})) > 0 \\
\implies &\sum_{i=1}^{m_T^*} \mathbb{E}[\mathrm{MB}_i(x')] - k(m_T^*) > \sum_{i=1}^{\underline{m_T}} \mathbb{E}[\mathrm{MB}_i(x')] - k(\underline{m_T}) \\
\implies &\mathbb{E}[\mathrm{TB}_{m_T^*}(x')] - k(m_T^*) > \mathbb{E}[\mathrm{TB}_{\underline{m_T}}(x')] - k(\underline{m_T})
\end{aligned}$$

and therefore the buyer's optimal number of entrants to recruit is nondecreasing in the clearing price.

We now address the supplier bidding strategy. Working backwards, in the second auction, the result holds as it is analogous to a single auction. In the test auction, if supplier $i$ remains in the auction at a price below his true cost $x_i$, he will lose money on any units he is awarded and can only make negative profit. If the supplier drops out of the test auction at a price above his true cost $x_i$, he loses the test auction and cannot make more profit in the second auction than if he bid down to $x_i$ because the number of entrants the buyer will recruit is nondecreasing in the outcome of the first auction. In either case, the supplier would have been better off remaining in the auction until winning or reaching his true cost, whichever happens first.

Note that the above analysis holds for any quantity auctioned off in the test auction. That is, the incumbent cost information gleaned by the buyer in the test auction is the same regardless of the quantity auctioned off in the test auction (as long as that quantity is at least $y$, the minimum quantity needed to entice the incumbents to participate in the auction). Thus, $y$ is the optimal quantity for the buyer to auction off in the test auction, since auctioning off more units does not change the buyer's information and would only possibly result in her paying more if she winds up recruiting entrants for the second auction.

### 2.6.2 Proof of Proposition II.2

When the reserve price is met and the clearing price is $x = \min\{r_1^*, X_{(2:n)}\}$, the buyer's optimal number of entrants to recruit for the second auction, $m_T^*$, is the minimizer of (2.3), i.e.,

$$m_T^* = \underset{m_T \in \mathbb{N}}{\arg\min} \left\{ \mathbb{E}[X_{(2:n+m_T)} | \min\{r_1^*, X_{(2:n)}\} = x](Q - y) + k(m_T) \right\}. \tag{2.16}$$

Now consider the test without reserve price strategy. When the clearing price of the first auction is $x'$, the optimal number of entrants for the buyer to recruit, say $m_T^{*'}$, is the minimizer of (2.1), i.e.,

$$m_T^{*'} = \underset{m_T \in \mathbb{N}}{\arg\min} \left\{ \mathbb{E}[X_{(2:n+m_T)} | X_{(2:n)} = x'](Q - y) + k(m_T) \right\}. \tag{2.17}$$

Note that the clearing prices of the test auctions in equations (2.16) and (2.17) are $x$ and $x'$, respectively. As the clearing price of the first auction is the starting bid of the second auction, if $x = x'$, then $\mathbb{E}[\min\{x, X_{(2:n+m_T)}\}|\min\{r_1^*, X_{(2:n)}\} = x] = \mathbb{E}[X_{(2:n+m_T)}|X_{(2:n)} = x']$ and $m_T^* = m_T^{*'}$.

### 2.6.3 Proof of Proposition II.3

**(i)(a)**. Although an increase in $y$ does not affect the buyer's cost under the no-test strategy, it weakly increases her expected cost under any given sample path using the test strategy. For $y = 0$, test is optimal as the buyer could achieve the same expected cost as the no-test strategy by recruiting $m_N^*$ entrants regardless of the outcome of the first test auction.

**(i)(b)**. As discussed in Proposition II.1's proof, the expected unit cost under the no-test strategy is decreasing discrete convex in the number of recruited suppliers and approaches $a$ as $n + m \to \infty$. As the marginal cost of recruiting an entrant is nondecreasing, there must exist a $n^*$ such that $m_N^* = 0 \ \forall \ n \geq n^*$. If $m_N^* = 0$, the test strategy is a weakly dominant strategy.

**(i)(c)**. We model the new supplier recruitment cost growing proportionately larger by letting $a \cdot k(m)$ denote the recruitment cost, and considering the constant $a$. As $k(1) > 0$, there exists a constant, $\overline{a}$, such that when $a = \overline{a}$ the buyer prefers the test strategy because $m_N^* = 0$, and the test strategy weakly dominates the no-test strategy. Further, test will be preferred for all $a > \overline{a}$ as $m_N^* = 0$ for all such $a$.

**(i)(d)**. First we establish the following lemma:

**Lemma II.9.** *Let the scaled distribution $\tilde{f}$ be such that $\tilde{f}(x) = f(x/\alpha)$. As $\alpha$ becomes large (that is, the distribution is scaled up), the buyer prefers the no-test strategy. Similarly, as $\alpha$ becomes small (that is, the distribution is scaled down), the buyer* *prefers the test strategy.*

*Proof of Lemma II.9.* We show that scaling up (down) the distribution by $\alpha$ is equivalent to scaling down (up) the recruitment cost function by $\alpha$. Then the result follows from part (i)(c).

Define scaled distribution $\tilde{F}(x) \triangleq F(x/\alpha)$, and scaled recruitment cost function $\tilde{k}(m) \triangleq \alpha k(m)$. Let $\tilde{X}_{(i:j)}$ represent the $i^{\text{th}}$-lowest order statistic out of $j$ draws from the distribution $\tilde{F}$. Then the buyer's problem given by the parameters $\tilde{F}$, $\tilde{k}(m)$, $Q$, $y$, and $n$ can be written as follows. For the no-test strategy,

$$\begin{aligned} \mathbb{E}_N[\text{cost}|m_N] &= \mathbb{E}[\tilde{X}_{(2:n+m_N)}]Q + \tilde{k}(m_N) \\ &= \alpha\mathbb{E}[X_{(2:n+m_N)}]Q + \alpha \cdot k(m_N) = \alpha\big(\mathbb{E}[X_{(2:n+m_N)}]Q + k(m_N)\big). \end{aligned} \tag{2.18}$$

The analysis for the test strategy is analogous. Thus, the problem with scaled parameters $\tilde{f}$ and $\tilde{k}(m)$ is equivalent to the original problem with all supplier and recruitment costs scaled by $\alpha$. $\square$

Now consider the effect of shifting the distribution by $\Delta$. A $\Delta$-shift of the suppliers' cost distribution is represented by the distribution $\tilde{f}$ with $\tilde{f}(x) = f(x + \Delta)$. It is trivial to show that such a shift will not change the buyer's strategy preference — it will simply decrease the expected cost of both strategies by $\Delta \cdot Q$.

Combining this result with Lemma II.9 completes the proof of (i)(d).

**(ii)**. The test with reserve price strategy results in an expected cost that is less than or equal to the buyer's expected cost under the test with no reserve price strategy as $r_1 = b$ is a feasible reserve price that results in the same expected cost as the test with no reserve price strategy. Thus, if the test with no reserve price strategy has an expected cost less than the no-test strategy, the test with reserve price strategy will also have an expected cost less than the no-test strategy.

### 2.6.4 Proof of Proposition II.4

We note that in applying the revelation principle, we suppose that all suppliers (including all possible entrants) report their type at the outset of the mechanism. One can think of each entrant's report as being locked in a box that the buyer will only open if she pays the associated cost to recruit that entrant. Given that the revelation principle allows us to focus on direct mechanisms, incentive compatibility constraint (2.8) can be stated as $u_i(x_i) \triangleq \max_{s_i}\{p_i(s_i) - x_i q_i(s_i)\}$. By the envelope theorem, this gives $u_i'(x_i) = -q_i(x_i)$, which implies that $u_i(x_i) = u_i(b) + \int_{x_i}^b q_i(s_i)ds_i$. Solving for $p_i(x_i)$ gives

$$p_i(x_i) = u_i(b) + \int_{x_i}^b q_i(s_i)ds_i + x_i q_i(x_i). \tag{2.19}$$

It is easy to check (e.g., Lemma 2 in Myerson (1981)) that, if (2.19) determines the payment rule, then $q_i$ nonincreasing implies that incentive compatibility constraint (2.8) holds. Similarly, if (2.19) determines the payment rule, then $u_i(b) \geq 0$ for all $i$ implies that the individually rationality constraint (2.7) holds. Given these observations, and the fact that integrating (2.19) over $X$ gives $\mathbb{E}_X[p_i(X)] = \mathbb{E}_X\left[u_i(b) + \psi(X_i)Q_i(X)\right]$, we can rewrite the buyer's mechanism design problem (2.6)–(2.10) as

$$\min_{Q_i(x), m_T(x^I)} \quad \mathbb{E}\left[k(m_T(X^I)) + \sum_{i=1}^{n+m_T(X^I)} u_i(b) + \sum_{i=1}^{n+m_T(X^I)} \psi(X_i)Q_i(X_i, X_{-i})\right] \tag{2.20}$$

$$\text{s.t.} \quad u_i(b) \geq 0 \qquad \forall i \tag{2.21}$$

$$q_i(\cdot) \text{ nonincreasing} \qquad \forall i \tag{2.22}$$

$$\sum_{i=1}^{n+m_T(x^I)} Q_i(x_i, x_{-i}) = Q \qquad \forall i, \forall x \tag{2.23}$$

$$Q_i(x_i, x_{-i}) \in \{0, y, y+1, \ldots, Q\} \forall x, \forall i. \tag{2.24}$$

Note that an optimal mechanism will have $u_i(b) = 0$ for all $i$. We now establish the following lemma.

**Lemma II.10.** *The optimal number of entrants to recruit, $m_T^*(x^I)$, is nondecreasing in the lowest-cost incumbent's cost, $x^I_{(1:n)}$, and constant in all other incumbents' costs, $x^I_{(2:n)}, x^I_{(3:n)}, \ldots, x^I_{(n:n)}$.*

*Proof of Lemma II.10* Since $\psi(\cdot)$ is increasing, the incumbent with the lowest virtual cost will be the lowest-cost incumbent. Note that $m_T^*(x^I)$ is not affected by the incumbents with costs $x^I_{(2:n)}, x^I_{(3:n)}, \ldots, x^I_{(n:n)}$ because they are "out of the running" and $Q_i^*(x_i, x_{-i}) = 0$ for these incumbents.

Similar to the proof of Proposition II.1, we must show (i) the buyer's total expected payment plus recruitment cost is discrete convex in $m_T$ and (ii) the expected marginal benefit of recruiting the $m^{\text{th}}$ entrant is nondecreasing in $x^I$.

Let $H$ be the distribution of $\psi(\cdot)$. Note that $\mathbb{E}[\psi(X_{(1:n+m)})|x^I_{(1:n)}] = \int_0^{\psi(x^I_{(1:n)})}(1 - H(x))^m dx$ is decreasing discrete convex in $m$. Since the supplier recruitment cost function is increasing convex in $m$, the buyer's expected total (recruitment plus purchase) cost is discrete convex in $m$. Next, note that the marginal reduction in expected purchase cost from recruiting the $m^{\text{th}}$ entrant equals

$$\mathbb{E}[\psi(X_{(1:n+m-1)})|x^I_{(1:n)}] - \mathbb{E}[\psi(X_{(1:n+m)})|x^I_{(1:n)}] = \int_0^{\psi(x^I_{(1:n)})}(1 - H(x))^{m-1}H(x)dx,$$

and the derivative of the right hand side with respect to $x^I_{(1:n)}$ equals $(1 - H(x^I_{(1:n)}))^{m-1}H(x^I_{(1:n)})$, which is positive. Thus, the buyer's optimal number of entrants to recruit is nondecreasing in $x^I_{(1:n)}$. $\square$

Having established this structural result on the recruitment rule, we next find the optimal mechanism.

**Lemma II.11.** *Let the number of entrants recruited by the buyer as a function of* $x^I$ *be given by* (2.11) *and let the allocation rule and payment rule, respectively, be given by:*

$$Q_i^*(x_i, x_{-i}) = \begin{cases} Q & \text{if} \quad x_i = x_{(1:n+m_T^*(x^I))} \\ 0 & \text{otherwise,} \end{cases} \tag{2.25}$$

$$P_i^*(x_i, x_{-i}) = \int_{x_i}^{b} Q_i^*(t_i, x_{-i})dt_i + x_i Q_i^*(x_i, x_{-i}). \tag{2.26}$$

*This constitutes an optimal mechanism.*

*Proof of Lemma II.11* Given a number of recruited entrant suppliers, $m_T(x^I)$, the optimal mechanism will minimize the third term of (2.20) by awarding $Q$ units to the lowest virtual cost supplier, per (2.25). Furthermore, as $m_T^*(x^I)$ given in (2.11) minimizes the buyer's objective function given the realization of the incumbent suppliers' costs, $x^I$, it must be optimal.

All that is left to verify are constraints (2.22)–(2.24). From (2.25) we see immediately that constraints (2.23) and (2.24) hold. We now show that $q_i$ is nonincreasing (constraint (2.22)). Suppose $i$ is an entrant supplier. Since supplier $i$'s report only affects the buyer's allocation decision (per (2.25)), which is to give the contract to the lowest-cost bidder, clearly entrant $i$ can not improve its allocation probability (increase $q_i$) by reporting a higher cost. Next suppose $i$ is an incumbent supplier. For any number of entrants recruited by the buyer, supplier $i$'s quantity allocation is nonincreasing in his cost report per (2.25). Moreover, the quantity allocation per (2.25) is nonincreasing in the number of recruited entrants he competes against. Since this number, $m_T^*$, is nondecreasing in supplier $i$'s report by Lemma II.10, we must have that supplier $i$ cannot increase his allocation probability by reporting a higher cost. In summary, the purchase quantity rule $q_i$ is nonincreasing in $x_i$ for all

$i$, so the mechanism is incentive compatible.

Given $Q_i^*(x_i, x_{-i})$, the optimal payment rule can be written as $P_i^*(x_i, x_{-i}) = \int_{x_i}^b Q_i^*(t_i, x_{-i})dt_i + x_i Q_i^*(x_i, x_{-i})$. As this mechanism satisfies incentive compatibility, individual rationality, and the quantity constraints, it is an optimal direct mechanism. $\square$

To complete the proof of Proposition II.4, we now show that the payment rule (2.26) can be equivalently written as (2.12).

First, equation (2.26) can be written as

$$P_i^*(x_i, x_{-i}|x_i < x_j \forall j \neq i) = \int_{x_i}^b Q_i^*(t_i, x_{-i})dt_i + x_i \cdot Q \tag{2.27}$$

Note that $Q_i^*(t_i, x_{-i}) = Q$ if $t_i = x_{(1:n+m_T^*(\tilde{x}^I))}$, and note that $m_T^*(\tilde{x}^I)$ may not necessarily equal $m_T^*(x^I)$ for all $t_i$: If the winning supplier is an incumbent and $t_i > x_i$, $m_T^*(\tilde{x}^I) \geq m_T^*(x^I)$ as $m_T^*$ is nondecreasing in $x^I_{(1:n)}$. Finally, note that $Q_i^*(t_i, x_{-i}) = 0$ for all $t_i > x_{(2:n+m_T^*(x^I))}$. Thus equation (2.27) becomes

$$\begin{aligned} P_i^*(x_i, x_{-i}|x_i < x_j \forall j \neq i) &= \int_{x_i}^{x_{(2:n+m_T^*(x^I))}} Q_i^*(t_i, x_{-i})dt_i + x_i \cdot Q \\ &= \int_{x_i}^{x_{(2:n+m_T^*(x^I))}} (1 - F(t_i))^{(m_T^*(\tilde{x}^I) - m_T^*(x^I))} \cdot Q dt_i + x_i \cdot Q \end{aligned}$$

which is equal to Proposition II.4's payment rule given by (2.12).

### 2.6.5 Proof of Proposition II.5

**(i)(a)**. Regardless of the suppliers' bidding strategies, for $y = 0$ the test strategy can do no worse in expectation than the no-test strategy: Under the test strategy, a feasible strategy is to always recruit $m_N^*$ entrants and not use the outcome of the test auction as a cap on the second auction, which achieves the expected cost of the no-test strategy.

**(i)(b)**. In Proposition II.3(i)(b), we found that the per-unit expected cost under the no-test strategy is decreasing discrete convex in the number of incumbent suppliers and approaches $a$ as $n \to \infty$ for the open-bid second-price auction. Under the no-test strategy, the bidders are ex ante symmetric so by the revenue equivalence theorem, the buyer will pay the same expected cost (up to a constant) under the open-bid second-price, sealed-bid first-price, and Dutch auction formats under no-test. Thus, as in Proposition II.3(i)(b), as the marginal cost of recruiting an entrant is nondecreasing, there must exist a $n^*$ such that $m_N^* = 0 \; \forall \; n \geq n^*$ for these auction formats. If $m_N^* = 0$, the test strategy is a weakly dominant strategy. This is because the buyer could replicate the outcome of the no-test auction by announcing that she will always recruit zero entrants after the test auction.

**(i)(c)**. The proof of Proposition II.3(i)(c) continues to hold, where as in part (i)(b) above we use the fact that test weakly dominates no-test when $m_N^* = 0$.

**(i)(d)**. The proof of Proposition II.3(i)(d) holds with the following change: Let $\mathsf{CP}$ and $\widetilde{\mathsf{CP}}$ represent the clearing price of a sealed-bid first-price or Dutch auction when suppliers have cost distribution $F$ and $\tilde{F}$, respectively. Then replacing $X_{(2:n+m_N)}$ and $\widetilde{X}_{(2:n+m_N)}$ with $\mathsf{CP}$ and $\widetilde{\mathsf{CP}}$, respectively, provides the result.

**(ii)**. The proof of Proposition II.3(ii) continues to hold.

### 2.6.6 Proof of Proposition II.6

**(i)**. Consider a supplier's bidding strategy under the no-test strategy and in the second auction of the test strategy. It is still a weakly dominant strategy for a supplier to remain in the auction until the price reaches their true cost for the same reasons as in Proposition II.1. Now consider the first test auction. Due to the restriction that only the incumbent supplier who is awarded units in the test auction can compete in the second auction, incumbent suppliers will not remove themselves from the test auction while the price is greater than their cost because they will lose the auction and will not be considered in future auctions. Further, incumbent suppliers will not stay in the auction when the price is less than their cost because they would make negative profit if they win the first auction, and the first auction's clearing price serves as a cap on the unit price of the second auction.

**(ii)**. Following the first test auction, the buyer aims to minimize her expected cost by choosing to recruit $m_T^*$ entrant suppliers, where $m_T^*$ is such that

$$m_T^* = \underset{m_T \in \mathbb{N}}{\arg\min} \left\{ \mathbb{E}[\tilde{X}_{(2:n+m_T)} | X_{(2:n)}, X_{(3:n)}, \ldots, X_{(n:n)}](Q-y) + k(m_T) \right\}$$

where $\tilde{X}$ has cumulative distribution function $\tilde{F}$, which represents the buyer's updated belief regarding the suppliers' cost distribution based on the realizations of the $n-1$ incumbent suppliers' drop-out costs, $X_{(2:n)}, X_{(3:n)}, \ldots, X_{(n:n)}$. Thus, $m_T^*$ is a function of the drop-out bids of the incumbent suppliers that do not win the first test auction.

### 2.6.7 Proof of Proposition II.7

**(i)(a)**. The proof of Proposition II.3(i)(a) continues to hold as the per-unit expected cost under the test strategy decreases in the number of suppliers regardless of the true distribution of $F$.

**(i)(b)**. As suppliers bid down to their true cost (see Proposition II.6) and as the true distribution of $F$ is regular, the expected clearing price is decreasing discrete convex in the number of bidders. Thus, the proof of Proposition II.3(i)(b) continues to hold.

**(i)(c)**. The proof of Proposition II.3(i)(c) continues to hold.

**(i)(d)**. The proof of Proposition II.3(i)(d) applies to the information updating case with one supplementation to Lemma II.9. Define the scaled distribution $\tilde{F}(x)$, scaled recruitment cost function $\tilde{k}(m)$, and $\tilde{X}_{(i:j)}$ as before. Let the $n-1$ incumbent drop-out bids be $b^{\mathsf{inc}} \triangleq [b_1, b_2, \ldots, b_{n-1}]$ (where $\mathsf{inc}$ stands for incumbent) and let the scaled version of the $n-1$ incumbent drop-out bids be $\widetilde{b}^{\mathsf{inc}} \triangleq b^{\mathsf{inc}}/\alpha = [b_1/\alpha, b_2/\alpha, \ldots, b_{n-1}/\alpha]$. Then, for any recruitment rule, the test strategy's equivalent to (2.18) is given by

$$\begin{aligned}
\mathbb{E}_T[\text{cost}] &= \mathbb{E}[\tilde{X}_{(2:n)}]y + \mathbb{E}_{\widetilde{b}^{\mathsf{inc}}}\left[\mathbb{E}[\tilde{X}_{(2:n+m_T(\widetilde{b}^{\mathsf{inc}}))}|\widetilde{b}^{\mathsf{inc}}](Q-y) + \tilde{k}(m_T(\widetilde{b}^{\mathsf{inc}}))\right] \\
&= \alpha\mathbb{E}[X_{(2:n)}]y + \mathbb{E}_{b^{\mathsf{inc}}}\left[\alpha\mathbb{E}[X_{(2:n+m_T(b^{\mathsf{inc}}))}|b^{\mathsf{inc}}](Q-y) + \alpha \cdot k(m_T(b^{\mathsf{inc}}))\right] \\
&= \alpha\left(\mathbb{E}[X_{(2:n)}]y + \mathbb{E}_{b^{\mathsf{inc}}}\left[\mathbb{E}[X_{(2:n+m_T(b^{\mathsf{inc}}))}|b^{\mathsf{inc}}](Q-y) + k(m_T(b^{\mathsf{inc}}))\right]\right).
\end{aligned}$$

**(ii)**. The proof of Proposition II.3(ii) continues to hold.

# CHAPTER III

# Entrant Cost Uncertainty and Pre-Auction Learning: Theory

## 3.1 Introduction

Manufacturing firms spend a significant amount of money procuring goods and services from outside suppliers in order to make their end products. According to a July 2013 CAPS Research report, industrial manufacturing firms' spend totaled over 54% of their revenues (CAPS Research, 2013). As a result, sourcing is often an area where buyers are interested in finding significant cost reductions through the promotion of competition between suppliers. Much of the sourcing literature addresses different sourcing mechanisms and considerations when a buyer is looking to lower her costs to source a good or service from a pool of *ex ante* symmetric suppliers. In practice, however, an incumbent supplier often has an informational advantage over a supplier who has not produced the good or service for the buyer. In this chapter, we study such a scenario through both theoretical and experimental lenses.

The specific scenario is as follows: A buyer has an established contract with a supplier for a specific good or service. We call the supplier that is currently fulfilling the contract the *incumbent supplier*. The contract for this item is coming up for bid; for example, in a production context a typical contract might last for a few years' supply of parts. An *entrant supplier* approaches the buyer, expressing an interest in winning business from the buyer. The buyer, who would like to gain price concessions from the incumbent or a lower price from the entrant than what she is currently paying the incumbent, would like to put the contract up for competitive bid and have the two suppliers compete for the business.

This is a natural and common occurrence in practice. In addition, when an incumbent faces an entrant in a competitive bidding event, interesting dynamics result from how well each party can predict their cost of fulfilling the buyer's contract. This interplay is especially relevant because a supplier's cost estimate is a critical input when it decides how much to bid for a contract.

The incumbent supplier — who has fulfilled the previous contract — has a good sense of her costs to continue supplying the good or service to the buyer due to her familiarity with the product. For example, the incumbent supplier may have already undergone extensive training with the buyer's engineers, determined her labor cost, secured licenses and certifications, or met stringent governmental regulations that are required to supply the good or service. Specifically, this knowledge results in the incumbent supplier's ability to calculate her own cost associated with the contract. By contrast, the entrant supplier does not have an at-the-ready prediction of his costs. For example, the contract might entail delivery schedules to specific buyer locations which would necessitate the entrant to consider these requirements and related infrastructure implications, and use this information to estimate his costs. Or, the contract up for bid might be for a non-standardized part with specific tolerances and the entrant might need to experiment with his existing production equipment to determine how costly it will be to produce the item, or to decide if he needs to purchase new equipment, which would require gathering of pricing information from equipment vendors. There are myriad additional possibilities, such as the cost of understanding and complying with any specific government regulations that might apply to the good or service. In short, the incumbent's previous experience may serve as a significant informational advantage over an entrant supplier who has not previously produced the good or service for the buyer.

While the entrant initially faces a cost information disadvantage, we consider the case where this uncertainty can be resolved by the entrant. For example, the entrant could engage in the initial phases of production planning in order to estimate his per-unit production cost of a complex part (see García-Crespo et al. (2011) for an overview of different cost estimation methods in manufacturing). Or, the entrant could hire an outside consultant to guide him in understanding the government regulations and costs involved with producing a part whose inputs are unusually toxic. However, while the entrant has the ability to erode the incumbent's cost information advantage by learning about his own costs, he must also weigh the expense of acquiring this information without a promise of winning the buyer's contract. This results in the entrant supplier facing a trade-off: He can invest costly effort to learn about his costs prior to competing with the incumbent for a contract to supply the good or service to the buyer, or he can initially bypass the investment (the "learning fee") and compete against the incumbent while at an informational disadvantage. This leads to our first research question:

**Research Question 1:** When does the entrant supplier find it preferable to resolve his cost uncertainty prior to bidding?

To investigate this research question, we analyze the entrant's learning strategy for different types of unknown costs. Our model reflects the fact that some costs can be the same for both the incumbent and the entrant — so-called *common cost* components, such as raw material costs or government taxes and inspection/licensing costs — while others are specific to each supplier — so-called *idiosyncratic cost* components, such as labor costs, utilization rates, or efficiency. One or the other might be easier for the entrant to estimate: For example, for a plastic injection molded part it might be easy to estimate the raw material resin cost (which is largely a function of part weight), but more difficult to estimate the production efficiency if the part has a complicated shape. Conversely, if the plastic part involves highly toxic inputs but is simple to manufacture, the government regulation costs may be difficult to estimate compared to the production efficiency, which is more straightforward.

We find that the entrant adopts a threshold learning fee policy when deciding whether to resolve his cost uncertainty prior to bidding. The threshold is independent of the entrant's common cost realization — he will choose to learn prior to bidding if the fee is less than a single threshold irrespective of the known common cost. However, the entrant's learning fee threshold is a function of his idiosyncratic cost. When the entrant knows his idiosyncratic cost but not the common cost, we find that the entrant is most likely to learn prior to bidding when he has a low-to-medium idiosyncratic cost realization; in such a case, the entrant highly values learning his unknown cost prior to competing against the incumbent.

Our next research question further builds off the intuition behind the entrant's learning decision by addressing the buyer's perspective and preference for the entrant's learning decision. Intuitively, a buyer could make it easier for the entrant to learn about his costs. For example, the buyer could provide a particularly comprehensive RFQ, which not only details the product specifications but also lists several possible methods of production. Of course, creating such a document requires the buyer to devote resources to flesh out these details, for which the buyer incurs a cost.

Thus, the buyer also faces a trade-off: The buyer may be able to increase competition between the incumbent and entrant by making it easier for the entrant to resolve his cost information disadvantage, but providing such assistance comes at a cost to the buyer. This results in:

**Research Question 2:** Does the buyer benefit from making it easier for the entrant to resolve his cost uncertainty prior to bidding, and if so, when?

We find that the buyer-optimal learning fee is a straightforward calculation in the unknown idiosyncratic cost case as the buyer is able to predict the entrant's learning decision based solely on the learning fee; the buyer will reduce the entrant's learning fee until the entrant is indifferent between learning and not learning unless the buyer's cost of fee reduction is too expensive. However, the buyer's choice of learning fee is much more complex in the unknown common cost case as the entrant's learning decision depends on his private information. The buyer must set the learning fee without knowledge of the entrant's threshold learning fee and thus cannot predict the entrant's actions for a given learning fee reduction.

Finally, we study the entrant's bidding and learning strategies and the implications for the buyer in a laboratory experiment and compare the findings to the theoretical predictions. Thus, we translated our model to a controlled laboratory setting in order to understand how these findings might actually play out in practice:

**Research Question 3:** To what extent are the theoretical predictions for our model replicated by actual behavior in a controlled laboratory experiment?

In the laboratory study, subjects play the role of the entrant supplier and make the corresponding learning and bidding decisions. The computer automates the role of the incumbent supplier. We find that subjects use a threshold-based learning strategy, but their threshold tends to be lower than the optimal threshold. As a result, subjects learn prior to the auction less often than theory predicts. Further, when subjects do not learn prior to bidding, they bid aggressively (i.e., less than the optimal bid) for most cost realizations; they bid greater than the optimal bid for extremely low idiosyncratic cost realizations when they do not know the common cost prior to bidding. The subjects' choices result in an important implication for the buyer: In our experiment, the costly reduction of the learning fee does *not* have a statistical impact on the buyer's costs. This suggests that buyers need not expend as much costly effort to make it easier for entrant suppliers to learn as theory predicts.

The remainder of this chapter is organized as follows. In §3.2, we summarize the related literature that addresses aspects of this research problem from both the theoretical and experimental viewpoints. In §3.3 we outline the model and discuss the incumbent supplier's bidding strategy. Sections 3.4 and 3.5 provide theoretical results for two different cases: First, we study the case where the entrant's information disadvantage stems from an idiosyncratic cost, while §3.5 addresses the case where the unknown cost is a common cost that is equal for both suppliers. In Chapter IV, we transition to studying the fourth research question in a controlled laboratory experiment and provide conclusions.

## 3.2 Literature Review

Our analysis addresses (i) the buyer's choice of whether to lower the learning fee and (ii) the entrant's subsequent learning strategy for a cost model that combines idiosyncratic and common cost components. In our model, it is costly for the buyer to reduce the entrant's learning fee due to the effort, time, and resources that are required to provide a more-detailed RFQ or other assistance. To our knowledge, we are the first to model the buyer's *costly* ability to control the entrant's learning fee.

By contrast, the literature that addresses the auctioneer's ability to release information to bidders assumes that it is a costless process for the auctioneer. For example, Eső and Szentes (2007) study the optimal auction when a seller can costlessly release signals of the buyers' valuations to the bidders and finds that the seller will fully reveal this information. Bergemann and Pesendorfer (2007) study the optimal auction when the seller costlessly determines the structure (precision) of the bidder's value information. The canonical work in this stream, Milgrom and Weber (1982), establishes the "linkage principle," which states that the auctioneer should always reveal available information in auctions with affiliated values. In our setting the buyer must balance the cost of making it easier for the entrant to learn cost information with the benefits provided by a reduced fee. Due to the this trade-off, the buyer does not necessarily choose to make it easier for the entrant to resolve his cost uncertainty. Moreover, in our model the buyer can prefer that the entrant does not learn, even if it would have been costless for the buyer to reveal information to the entrant. This occurs when the entrant's idiosyncratic cost (rather than the common cost) is unknown. Nonetheless, there is evidence that it may be advantageous for the buyer to assist the disadvantaged bidders even when such assistance is costly — for example, Rothkopf et al. (2003) finds that subsidizing bidders at an *economic* disadvantage can lower the buyer's expected cost. However, the entrant in our model has an *information* disadvantage.

Others have studied different ways the auctioneer can influence a bidder's learning strategy. For a single agent setting, Crémer et al. (1998a) and Crémer et al. (1998b) study how a principal can design a mechanism to induce the optimal amount of learning by the agent, and Shi (2012) extends this concept to multiple agents. These papers assume that the principal and the agent possess the same information about the agent's valuation before the agent decides to learn. By contrast, we allow for the realistic possibility that — even before learning — the agent can have superior information about its own cost compared with the principal. As in our case, they find that the agent chooses to learn if the cost is sufficiently low; however, in their models the agent does not have a known cost realization in addition to the unknown cost. Our model incorporates known costs and we find that the realization influences the entrant's learning decision in the known idiosyncratic cost case, while it does not influence the entrant's decision in the known common cost case. Further, Crémer et al. (1998a) find that the principal would like to induce the agent to learn when the learning cost is low; although we find that this is the case for the unknown common cost case, we find the opposite result when there is an unknown idiosyncratic cost.

Our discussion of the entrant's learning strategy fits in the costly information acquisition literature. Previous research in the operations management and economics fields have mainly focused on the common cost model, while we analyze the case where the entrant's total cost is the sum of a common cost and an idiosyncratic cost. Chatterjee and Harrison (1988) study an information collection problem motivated by the timber industry. They use a pure common values model and find equilibrium learning and bidding strategies when bidders can make costly observations. Persico (2000) finds that bidders choose to learn more information in first price auctions than in second price auctions in a common values setting. However, neither of these papers study the impact of a private cost component or allow the auctioneer to control the learning fee. Hernando-Veciana (2009) studies information acquisition in a combined idiosyncratic plus common value model where ex ante symetrically-informed bidders make simultaneous learning decisions; in our model, an uninformed entrant competes against an informed incumbent. Hernando-Veciana focuses on the implications for sealed- versus open-bid auctions and finds that bidders in open-bid auctions learn less about common values and more about private values than in sealed-bid auctions. Further, Hernando-Veciana's paper does not allow the auctioneer to influence the learning fee.

The costly information acquisition problem has also been studied under two related motivations. The research and development literature contains models where suppliers can make pre-auction investments before formulating their bid. However, in such papers (e.g., Tan (1992), Piccione and Tan (1996), and Arozamena and Cantillon (2004)) the investment allows the supplier to reduce their cost; that is, the investment affects the supplier's cost distribution. In contrast with these papers, we focus on intrinsic uncertainty in the cost itself. McAfee and McMillan (1987), Levin and Smith (1994), and Samuelson (1985) study auctions where bidders incur costs to participate in the competition. In this entry fee literature, the bidder *must* pay the fee to enter the auction; the entrant in our model can participate in the auction if he does not pay the learning fee.

The behavioral literature also touches on certain aspects of our model; however, to the best of our knowledge we are the first to experimentally study the entrant's information acquisition problem in an auction setting. Kagel and Levin (2002) provide an excellent overview of subjects' bidding behavior in a variety of common-value auction settings. A fair amount of experimental literature has studied bidding behavior in second price auctions. Avery and Kagel (1997) study second price common-value auctions where one bidder has a private value advantage (i.e., the bidders have asymmetric payoffs as one bidder has a known private value in addition to the common value). They find that the disadvantaged bidder tends to bid much more aggressively than the equilibrium bidding strategy. In our model, the entrant's main disadvantage stems from his cost uncertainty, which can be resolved at a cost; further, the entrant may face a cost advantage or disadvantage based on his idiosyncratic cost realization.

In the private values setting, Cooper and Fang (2008) study bidding in private value auctions where the subject receives noisy signals regarding the opponents' valuations. They find that subjects tend to overbid (i.e., bid aggressively), albeit by different amounts based on the signal. In our case, the subjects' uncertainty is caused by their knowledge of their own cost. Cantillon (2008) and Güth et al. (2005) address the case where bidders have asymmetrically-distributed valuation distributions within a private values auction framework. However, these studies do not allow the subject to resolve their uncertainty at a cost, which is a crucial component of our experiment.

Kraemer et al. (2006) addresses costly learning in a non-auction setting. They find that the subjects generally purchase too many information signals in a sequential decision-making model. By contrast, earlier work by Rötheli (2001) found that subjects underestimate the value of information when they can sequentially learn multiple pieces of possibly-correlated information. However, in our model we focus on learning in a competitive (auction) context, and we model the decision to "purchase" information as a binary decision.

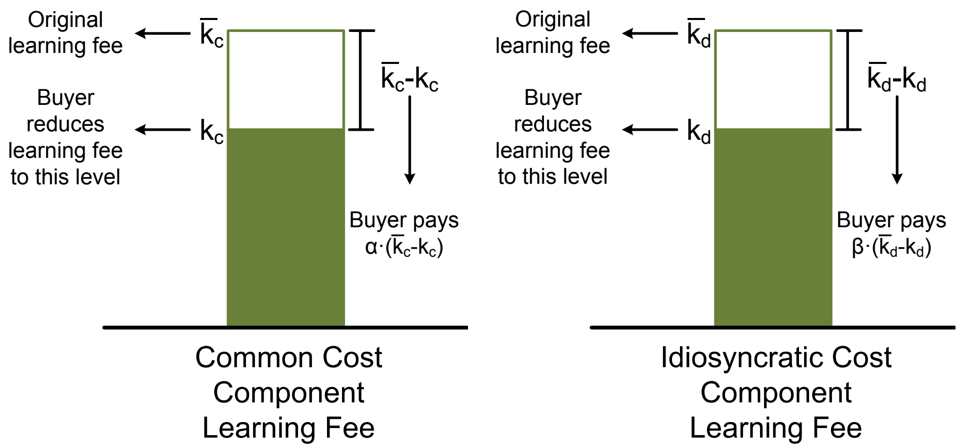
Finally, the behavioral operations management literature contains papers that address learning in a sequential search setting. Bearden et al. (2006) and Palley and Kremer (2014) study search and learning in a rank-based version of the secretary's problem, where the subject receives ordinal information regarding the value of an item and must decide whether to either stop the search and keep the item or decline the item. However, our model results in the entrant *bidding* based on his learning decision and cost information, and the entrant becomes perfectly informed if he chooses to learn. In Chapter IV, we discuss other relevant experimental papers in the context of our findings.

### 3.3 Model

We consider an incumbent supplier and an entrant supplier (supplier $i$ and $e$, respectively) competing to supply a contract to a buyer. The buyer will award the contract via an open-bid, descending-price auction. In practice, this is often called a "clock auction." Each supplier is risk-neutral and has a linear production cost that is the sum of two independent stochastic components: a common cost component and an idiosyncratic cost component. Both suppliers have the same common cost component $c$, which has cumulative distribution $F$ with support $[\underline{c}, \overline{c}]$. For example, the common cost may represent the cost of a commodity input, tooling, or obtaining licenses and governmental approval to produce the item or service. The idiosyncratic cost components of the incumbent and entrant are given by $d_i \sim G_i$ with support $[\underline{d_i}, \overline{d_i}]$ and $d_e \sim G_e$ with support $[\underline{d_e}, \overline{d_e}]$, respectively. These idiosyncratic costs are independent and may represent a combination of the labor, transportation, or yield-dependent costs. Thus, the total production cost for the incumbent is $c + d_i$, and the total production cost for the entrant is $c + d_e$. Let $f$, $g_i$, and $g_e$ be the corresponding probability distribution functions; we assume they are strictly positive and continuous on their respective supports.

The incumbent knows the values of $c$ and $d_i$ through her experience as a supplier to the buyer — perhaps the buyer is sourcing an item that she sourced from the incumbent in the past or the incumbent made a previous generation or similar version of the product. The buyer, however, is unaware of the incumbent's costs. It is common in practice for a supplier to carefully guard its cost information from the buyer. The buyer is aware of the cost distributions $F$, $G_i$, and $G_e$.

The entrant initially only knows *one* of his two costs (either the common cost or his idiosyncratic cost): He must spend time and money on prototypes, design specifications, financial calculations, consultant fees, and similar procedures to learn the realization of the other cost. The entrant can learn the unknown cost realization by paying a learning fee. The entrant's learning fee to resolve his cost uncertainty is initially equal to $\overline{k_c}$ and $\overline{k_d}$ in the unknown common cost and unknown idiosyncratic cost cases, respectively. However, the buyer has the ability to reduce the learning fee that the entrant ultimately incurs. Specifically, in the unknown common cost case the buyer's cost to set the common cost component's learning fee equal to $k_c$ is $\alpha(\overline{k_c}-k_c)$, where $\overline{k_c} \geq k_c$ is the default learning fee if the buyer does not adjust the fee (see Figure 3.1(a)). In practice, setting the learning fee can involve releasing information such as drawings, prototypes, and allowing access to the firm's engineers. The buyer may also expend time and money on making the item's specifications more precise or providing references to different production techniques for making the part. Here, $\alpha$ is a parameter that represents how costly it is for the buyer to make it easier for the entrant to learn – if $\alpha = 0$, then it is free for the buyer to make the learning easier (for example, he just releases information that he has already prepared), while if $\alpha = 1$ the buyer must fully subsidize the $\overline{k_c} - k_c$ decrease in the common component's learning fee. Likewise, in the unknown idiosyncratic cost case the buyer's cost to set the idiosyncratic cost component's learning fee equal to $k_d$ is $\beta(\overline{k_d} - k_d)$, where $\beta$ represents the fraction of the idiosyncratic cost learning fee decrease incurred by the buyer (see Figure 3.1(b)). We restrict $\alpha$ and $\beta$ to nonnegative values to capture the fact that exerting effort is costly for the buyer.




(a) The buyer incurs a cost of $\alpha \cdot (\overline{k_c} - k_c)$ to reduce the entrant's common cost learning fee from the default value of $\overline{k_c}$ to $k_c$.

(b) The buyer incurs a cost of $\beta \cdot (\overline{k_d} - k_d)$ to reduce the entrant's idiosyncratic cost learning fee from the default value of $\overline{k_d}$ to $k_d$.

Figure 3.1: Buyer's reduction of the entrant's learning fees.

Second, we assume that $k_c \leq \overline{k_c}$ and $k_d \leq \overline{k_d}$; that is, the buyer cannot make it more expensive for the entrant to learn his cost. It is best to think of the default learning fees $\overline{k_c}$ and $\overline{k_d}$ as large values that represent the minimal required amount of information needed by a supplier in order to participate in an auction. At the very least, the buyer must provide an RFQ that details the specifications of the good or service, expected delivery date, and similar necessary pieces of information. Thus, the default learning fee corresponds to this minimum level of information required by an entrant to bid. Finally, we assume that the buyer "sets" the final value of the learning fee before the entrant supplier has to make any decisions; that is, the buyer implicitly sets the learning fee when she announces the RFQ and provides the corresponding information (e.g., drawings, prototypes, references) to the entrant before the entrant decides whether to incur the learning fee.

Because $d_i$ and $d_e$ are independent, learning his idiosyncratic cost component ($d_e$) does not give the entrant any additional information regarding the incumbent's idiosyncratic cost – he only knows the distribution of $d_i$. He may choose to learn or not learn a given piece of information prior to the auction. We assume that if the entrant wins the auction without learning a piece of information, he has to incur the cost of learning this information before supplying the item. This is because the knowledge gained through learning $c$ and $d_e$ is necessary to produce the item to the buyer's specifications. For example, the entrant may need to negotiate pricing of an input or commodity, refine production techniques for the product in question, or obtain necessary permits or certifications prior to production.

Before proceeding with the analysis of the entrant's learning strategies, note that it is a weakly dominant strategy for the incumbent supplier to use bid-down-to-level (drop-out bid) $c + d_i$. Namely, it is optimal for the incumbent to stay in the auction until the price reaches her true cost regardless of the entrant supplier's actions (see, e.g., Krishna (2002)).

### 3.4 Unknown Idiosyncratic Cost Case

In this section, we analyze the case where the entrant supplier's cost information disadvantage surrounds his idiosyncratic cost component, $d_e$. Prior to competing in the auction against the incumbent, the entrant knows the common cost realization, $c$, and his idiosyncratic cost distribution function, $G_e$. Such a situation is prevalent in many industries where the common costs stem from commodities and widely-available inputs. For example, it may be easy for the entrant supplier to estimate the cost of raw materials necessary to produce the part given the metal recipe and part weight (which constitutes a common cost). However, in such a case it may be difficult for the buyer to know how easily the parts can be produced using his current machinery, which obfuscates his idiosyncratic cost component. The entrant can choose to learn his idiosyncratic cost component by paying the learning fee, $k_d$, which is set by the buyer before the entrant's learning decision is made.

If the entrant chooses to incur the learning fee prior to bidding, he learns $d_e$ and then competes in the auction. If the entrant wins the auction (i.e., if the incumbent drops out of the auction first) then he supplies the good or service and is paid the drop-out bid of the incumbent; if the entrant is the first to drop out of the auction, the incumbent wins the contract and the entrant receives zero revenue.

If the entrant chooses *not* to learn $d_e$ prior to competing in the auction, he must prepare his bid-down-to-level based on his knowledge of $c$, $G_e$, and $k_d$. If the entrant wins the auction, he is paid the drop-out bid of the incumbent and incurs three costs while supplying the good or service to the buyer: (1) the learning fee, $k_d$, is incurred because the knowledge that is gained through incurring this fee is necessary to produce the item to the buyer's specifications (e.g., refining production techniques); (2) his idiosyncratic cost, $d_e$, and (3) the common cost, $c$. Finally, if the entrant loses the auction, he does not produce the item and receives zero revenue. This sequence of events is illustrated in Figure 3.2.

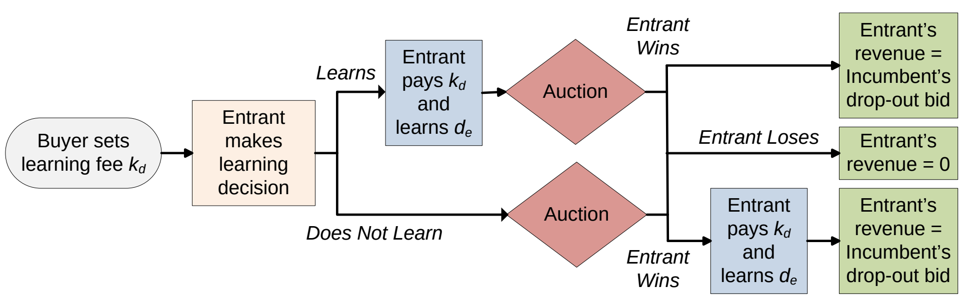



Figure 3.2: The sequence of events when the entrant does not initially know his idiosyncratic cost realization, $d_e$.

To analyze when it is optimal for the entrant to learn his idiosyncratic cost component before the auction, we quantify the entrant's expected profit as a function of his learning decision. Similarly, we determine the buyer's expected cost given the entrant's learning decision as a step towards finding the buyer's optimal learning fee that is set at the outset of the procurement process. Throughout the remainder of the chapter, we use the following notation when expressing the entrant's profit and bidding functions and the buyer's expected cost function: Subscript $c$ refers to the case where the entrant knows the common cost ($c$) but not his idiosyncratic cost, while subscript $cd$ refers to the case where the entrant knows both his commmon and idiosyncratic costs ($c + d_e$). In §3.5 we will use a subscript $d$ to represent the case where the entrant knows his idiosyncratic cost but not the common cost realization.

We can now express the entrant's expected profit when he chooses to learn his idiosyncratic cost prior to the auction, $\mathbb{E}[\Pi_{cd}(b_{cd}(c, d_e))]$ as a function of his bid ($b_{cd}(c, d_e)$), which only depends on his known costs (the common cost and his idiosyncratic cost realization):

$$\begin{aligned} &\mathbb{E}[\Pi_{cd}(b_{cd}(c, d_e))] \\ &\quad = -k_d + \mathbb{E}_{d_i,d_e}[c + d_i - (c + d_e)|c + d_i \geq b_{cd}(c, d_e)] \cdot \Pr(c + d_i \geq b_{cd}(c, d_e)). \quad (3.1) \end{aligned}$$

Note that the entrant's bid affects his profit through the *probability* that the entrant wins the auction and not his payment *given the outcome* of the auction. Similarly, the entrant's expected profit when he does not pay the learning fee prior to the auction, $\mathbb{E}[\Pi_c(b_c(c))]$, is given by

$$\mathbb{E}[\Pi_c(b_c(c))] = \mathbb{E}_{d_i}[c + d_i - (c + \mathbb{E}[d_e] + k_d)|c + d_i \geq b_c(c)] \cdot \Pr(c + d_i \geq b_c(c)). \quad (3.2)$$

Here, we note an interesting consequence of the structure of the descending-price open-bid auction format: Under a clock auction, the entrant's bid simply determines whether the entrant *wins* the auction; conditional on the outcome of the auction, the entrant's revenue and costs are independent of his own bid. To move towards determining the entrant's learning strategy, we describe the entrant's optimal bidding strategies under both learning decisions.

**Proposition III.1.** *Suppose the entrant knows the common cost, c. If the entrant pays the learning fee $k_d$ to learn his idiosyncratic cost realization prior to the auction, the entrant's optimal bid-down-to-level is his total production cost, $b^*_{cd}(c, d_e) = c + d_e$. If the entrant does not pay the learning fee prior to the auction, the entrant's optimal bid-down-to-level is $b^*_c(c) = c + \mathbb{E}[d_e] + k_d$, namely, his total expected production cost plus the learning fee.*

To summarize the two bidding strategies, this result states that the entrant bids down to his total (expected) cost associated with *producing* the good or service given that he wins the auction: When the entrant chooses to learn $d_e$ prior to the auction, the learning fee is "sunk" regardless of the outcome of the auction. As a result, the entrant aims to maximize his expected profit given his production cost, $c + d_e$, and bids down to that cost. We note that this bidding strategy is the same as the incumbent's bidding strategy. If the entrant chooses not to learn $d_e$ prior to the auction, his expected cost to produce the item given that he wins the auction consists of the known common cost, his expected idiosyncratic cost, and the learning fee that is incurred if he wins the auction (and not incurred if he loses the auction). The entrant's unknown cost is independent of the incumbent's private information, so the entrant's optimal bidding strategy entails attempting to win the auction if and only if the clearing price of the auction (i.e., the incumbent's total cost) is greater than his own total expected cost.

### 3.4.1 Entrant's Learning Decision

Given the entrant's optimal bidding strategies, we now analyze when it is optimal for the entrant to pay the learning fee prior to the auction. The entrant's optimal bid when he learns $d_e$ is $b^*_{cd}(c, d_e) = c + d_e$, while his optimal bid is given by $b^*_c(c) = c + \mathbb{E}[d_e] + k_d$ when the entrant chooses not to learn the idiosyncratic cost prior to the auction. Incorporating $b^*_{cd}$ and $b^*_c$ into (3.1) and (3.2), respectively, results in the entrant's expected profit under both options:

$$\begin{aligned}
\mathbb{E}[\Pi_{cd}] &= -k_d + \mathbb{E}_{d_i,d_e}[d_i - d_e | d_i \geq d_e] \cdot \Pr(d_i \geq d_e) \\
&= -k_d + \mathbb{E}_{d_i,d_e}[(d_i - d_e)^+] \qquad (3.3) \\
\mathbb{E}[\Pi_c] &= \mathbb{E}_{d_i}[d_i - (\mathbb{E}[d_e] + k_d) | d_i \geq \mathbb{E}[d_e] + k_d] \cdot \Pr(d_i \geq \mathbb{E}[d_e] + k_d) \\
&= \mathbb{E}_{d_i}[(d_i - (\mathbb{E}[d_e] + k_d))^+] \qquad (3.4)
\end{aligned}$$

where $(\cdot)^+$ represents the nonnegative value of the term in the parentheses.

Before proceeding with the analysis of the entrant's idiosyncratic cost learning decision, we consider the entrant's tradeoffs between learning and not learning prior to the auction. First consider the case where $k_d$ is zero – the idiosyncratic cost information is free for the entrant. In the case of free information, the entrant would choose to learn his idiosyncratic cost prior to the auction for two reasons: First, learning helps the entrant avoid winning the contract at a loss if he is awarded the contract and later discovers that his idiosyncratic cost results in a total cost greater than the clearing price of the auction. Second, learning helps the entrant guard against forgoing a contract which would have been profitable if the entrant knew his idiosyncratic cost *a priori*. Now consider the case where $k_d > 0$. When idiosyncratic cost information is costly for the entrant, the entrant's decision is unclear: He benefits from learning the cost information for the reasons above, but paying the learning fee prior to the auction comes with risks. First, the entrant might learn his idiosyncratic cost is high and lose the auction, but he may have also lost the auction if he did not learn. Alternatively, he may realize a lower-than-expected idiosyncratic cost but still lose the auction to the incumbent. Under both of these scenarios, the entrant would have saved the learning fee if he did not learn his cost prior to the auction and instead bid according to his expected cost.

Given this discussion, one may expect that the entrant will learn his idiosyncratic cost prior to the auction if the information cost is small. Indeed, we now show a fundamental result for this problem, which states that there is a single threshold learning cost, $\widetilde{k_d}$, such that the entrant chooses to learn his cost prior to bidding if and only if his learning cost is less than the threshold.

**Proposition III.2.** *There exists a threshold learning fee, $\widetilde{k_d} \geq 0$, such that the entrant chooses to learn the realization of $d_e$ prior to the auction if and only if $k_d \leq \widetilde{k_d}$.*

Here, $\widetilde{k_d}$ represents the idiosyncratic learning fee that results in the entrant being indifferent between learning and not learning prior to the auction. When the idiosyncratic learning fee is low, the information that the entrant reveals through the learning process is more valuable than bidding without this information. Learning allows the entrant to bid aggressively if he discovers a low cost, while learning that he has a high idiosyncratic cost component before the auction prevents the entrant from underbidding and losing money. However, as the cost of learning this information increases, the benefits of learning the information diminish.

We also note that the threshold learning fee is independent of the common cost information known to both suppliers; in fact, the threshold only depends on the idiosyncratic cost distributions. The threshold is independent of the common cost realization, $c$, because both suppliers know the common cost *a priori* and incorporate its realization into their bids. Hence, whether the suppliers have a low, medium, or high common cost realization does not affect the entrant's decision of whether to learn his idiosyncratic cost.

### 3.4.2 Buyer-Optimal Learning Fee

Our results surrounding the supplier's optimal bidding strategies and the entrant's threshold-based learning decision now allow us to find the buyer-optimal learning fee, or the learning fee that minimizes the buyer's total expected cost of procuring the good or service. Given the entrant's bidding strategies, the buyer's expected costs as a function of the learning fee under the entrant's learn and bid without learning strategies, $\mathbb{E}[\Omega_{cd}(k_d)]$ and $\mathbb{E}[\Omega_c(k_d)]$, respectively, are given by

$$\mathbb{E}[\Omega_{cd}(k_d)] = \mathbb{E}[c] + \mathbb{E}[\max\{d_i, d_e\}] + \beta(\overline{k_d} - k_d) \tag{3.5}$$

$$\mathbb{E}[\Omega_c(k_d)] = \mathbb{E}[c] + \mathbb{E}[\max\{d_i, \mathbb{E}[d_e] + k_d\}] + \beta(\overline{k_d} - k_d). \tag{3.6}$$

First, recognize that the buyer's selection of $k_d$ will determine whether the entrant learns his idiosyncratic cost realization prior to the auction: The entrant will learn prior to the auction if and only if $\mathbb{E}[\Pi_{cd}] \geq \mathbb{E}[\Pi_c]$ for the given learning fee. Thus, the buyer-optimal learning fee will incorporate the buyer's preference of whether the entrant learns $d_e$ before the auction. To build this intuition, we once again consider the case where the buyer has already chosen $k_d = 0$. When information is free, the buyer prefers that the entrant does not learn his idiosyncratic cost prior to the auction. To see this result, consider the buyer's expected cost under both scenarios. If the entrant chooses to learn, the buyer's expected cost is $\mathbb{E}[c]+\mathbb{E}[\max\{d_i, d_e\}]+\beta(\overline{k_d}-k_d)$; if the entrant does not learn, the buyer's expected cost is $\mathbb{E}[c]+\mathbb{E}[\max d_i, \mathbb{E}[d_e]]+\beta(\overline{k_d}-k_d)$. As the maximum function is convex, Jensen's Inequality implies that the buyer's expected cost when the entrant does not learn is less than the alternative. Thus, the buyer will *not* want the entrant supplier to learn his idiosyncratic cost when learning is free. Now consider the case where $k_d > 0$. If the entrant chooses not to learn, he will incur the learning fee if and only if he wins the auction; as a result, the entrant incorporates $k_d$ into his bid. However, if the entrant learns prior to the auction, the learning fee is sunk and excluded from the entrant's bid. Thus, the entrant's bid when he chooses to learn *after* the auction incorporates a positive term that is disregarded when the entrant chooses to learn. For this reason, the buyer may prefer that the entrant learns prior to the auction.

This naturally leads to the question: If the buyer could force the entrant to learn his idiosyncratic cost prior to the auction, when would she force the entrant to learn? In the following result, we establish that the buyer and the entrant have "competing objectives" — that is, when the entrant prefers not to learn his idiosyncratic cost prior to the auction, the buyer would rather the entrant learn his cost (and vice versa).

**Proposition III.3.** *For all common cost realizations and idiosyncratic cost distributions there exists a threshold idiosyncratic learning fee, $\widehat{k_d} \geq 0$, such that the buyer prefers that the entrant learns his idiosyncratic cost realization if and only if $k_d \geq \widehat{k_d}$. Further, $\widehat{k_d} = \widetilde{k_d}$; that is, if the buyer prefers that the entrant learns (does not learn) his idiosyncratic cost for a given $k_d$, the entrant does not want to learn (wants to learn) his idiosyncratic cost. If $k_d = \widehat{k_d}$, the buyer and the entrant are indifferent to the entrant's learning decision.*

The fact that the entrant and the buyer prefer opposite learning strategies for a given $k_d$ can be understood by thinking of our model in the context of a zero-sum game. For a fixed $k_d$, the buyer's expected cost consists of her expected payment to the incumbent plus her expected payment to the entrant. Meanwhile, the entrant's expected profit is a function of his expected payment and his expected cost (given that he wins the auction). Intuitively, if an entrant prefers a certain learning strategy because it results in a larger expected profit, the buyer will dislike that strategy for the same reason.

The entrant has the prerogative to choose whether to learn prior to the auction for a given $k_d$. As a result, one may initially conclude that the buyer will be at the mercy of the entrant's decision, and will always experience the outcome that results in her paying a greater expected cost. However, the buyer's ability to set the learning fee by releasing information at a cost of $\beta(\overline{k_d} - k_d)$ can allow her to effectively predetermine the entrant's learning strategy.

We now examine the buyer-optimal idiosyncratic learning fee, $k_d^*$. The buyer's choice of $k_d^*$ depends on the proportion of the learning fee decrement that she has to pay, $\beta$. For a given $\beta$, the buyer trades off the cost of subsidizing the entrant's learning, $\beta(\overline{k_d} - k_d)$, with the potential savings when the entrant chooses to "sink" the learning fee and learn $d_e$ prior to the auction.

The buyer wants to select the learning fee that minimizes her expected cost given the entrant's decision of whether to learn the information prior to the auction or after the auction (if the entrant wins the contract). Proposition III.3 established that the buyer and entrant have opposite preferences; this result provides two insights into the buyer's choice of learning fee. First, note that if the entrant supplier would choose to learn his idiosyncratic cost for a given learning fee, the buyer would not want the entrant to learn. However, the buyer cannot prevent the entrant from learning by further reducing the learning fee due to the entrant's threshold result from Proposition III.2. Thus, the buyer will never incur costs to reduce the learning fee if the entrant would learn for a given fee; if the buyer paid a reduction cost, the entrant would continue to learn for the reduced fee but have the same bid-down-to-level in the auction ($c+d_e$). On the other hand, if it is not optimal for the entrant to learn for a given learning fee — and hence the buyer prefers the entrant would learn for such a fee — the buyer can induce the entrant to learn by reducing the learning fee. Given these insights, we now address the buyer-optimal learning fee.

**Proposition III.4.** *The buyer will reduce the idiosyncratic learning fee to*

$$k_d^* = \min\{\max\{\widetilde{k_d}, G_i^{-1}(\beta) - \mathbb{E}[d_e]\}, \overline{k_d}\}. \tag{3.7}$$

First, consider the outer term: The $\min\{\cdot\}$ term confirms the aforementioned intuition. When the entrant chooses to learn prior to the auction under the "default" learning fee of $\overline{k_d}$ (i.e., when $\widetilde{k_d} > \overline{k_d}$), the buyer will not reduce the learning fee because any reduction will simply be a savings passed onto the entrant without any benefit — the entrant is willing to pay $\overline{k_d}$ and will bid his cost irrespective of the learning fee because that cost is sunk.

However, if the entrant will choose not to learn under the default learning fee $\overline{k_d}$, the buyer may reduce the learning fee. Such a reduction may be beneficial when the entrant does not learn prior to the auction because the learning fee is incorporated into the entrant's bid of $c+\mathbb{E}[d_e]+k_d$. In this case, the optimal learning fee is captured by the $\max\{\cdot\}$ term. The intuition behind this term is as follows: Because the buyer and the entrant have opposing preferences (i.e., the buyer and the entrant each want the entrant to make the opposite learning decision), the buyer will reduce the learning fee to the fee that makes the entrant indifferent to learning and not learning ($\widetilde{k_d}$) *unless* such a reduction is too costly. In the case that the fee reduction to $\widetilde{k_d}$ is too costly, the buyer reduces the learning fee until the reduction costs outweigh the savings (which occurs when $k_d^* = G_i^{-1}(\beta) - \mathbb{E}[d_e]$). This equation represents the learning fee where the buyer's marginal cost of reducing the learning fee ($\beta$) equals her marginal benefit. The buyer's marginal benefit is represented by $G_i(\mathbb{E}[d_e] + k_d)$, the probability that the entrant *loses* the auction and thus sets the clearing price: For a given sample path, the buyer will realize a decrease in procurement cost only if the entrant sets the price — if the entrant wins the auction, the buyer will pay $c + d_i$ regardless of the entrant's bid. As a unit reduction in the learning fee results in a unit reduction in the entrant's bid, the buyer's expected savings from reducing the entrant's learning fee is therefore equal to the probability that the entrant sets the price.

One important implication of this result states that if the buyer has to pay at least the full amount of the learning fee reduction (i.e. $\beta \geq 1$), the buyer has no incentive to reduce the learning fee. While a reduced learning fee will result in a bid that is $(\overline{k_d} - k_d)$ less in expectation when the entrant is induced to learn prior to the auction, the buyer has to pay $\beta(\overline{k_d} - k_d)$ up front, hence erasing the benefits.

## 3.5 Unknown Common Cost Case

We now address the case where the entrant is less informed of the common cost component and must decide whether to pay the common cost learning fee prior to the auction. Prior to making this learning decision, the entrant knows his own idiosyncratic cost realization, $d_e$, and the common cost's cumulative distribution, $F$. For example, the entrant may know his own internal production costs (e.g., his labor cost and typical yield rate for the item up for bid) but still needs to investigate the raw material costs or the necessary licenses and certifications associated with the contract. The entrant can learn the common cost realization (which is already known to the incumbent) by incurring the learning fee, $k_c$, which is set by the buyer at the outset of the procurement process. The sequence of events mirror Figure 3.2, with $k_c$ and $c$ replacing $k_d$ and $d_e$, respectively.

To analyze the unknown common cost case, we take the same steps as in §3.4 — we establish the entrant's bidding strategies and study the entrant's optimal learning decision, and then analyze the buyer's optimal learning fee. The nature of the unknown cost information alters these decisions compared to the results of §3.4. In §3.4, the only information discrepancy surrounds private, independent cost values. The cost component that the entrant knew up-front — the common cost — was a cost that was equal for both suppliers. By contrast, here the differences between the suppliers' knowledge of the common cost results in an added layer of complexity due to the correlation between the entrant's unknown cost component and the incumbent's total cost. Unlike in the previous case where the entrant's known common cost was equal to the incumbent's common cost, the entrant may believe that his idiosyncratic cost realization provides a cost advantage (if he has a low realization) or disadvantage (if he has a high realization).

Given the learning fee, $k_c$, the entrant must initially decide whether to learn the common cost prior to the auction. If the entrant learns prior to participating in the auction, he will pay $k_c$, learn the common cost to fulfill the contract, and thus know his true cost of supplying the good or service: $c + d_e$. The entrant's expected profit for this case is the same as equation (3.1) from §3.4; thus, the first result from Proposition III.1 holds and the optimal bidding strategy when the entrant learns the common cost (and thus his total cost) prior to the auction is $b^*_{cd}(c, d_e) = c + d_e$.

When the entrant does not learn prior to the auction, his expected profit,

$\mathbb{E}[\Pi_d(b_d(d_e))]$, is

$$\begin{aligned}\mathbb{E}[\Pi_d(b_d(d_e))] &= \mathbb{E}_{c,d_i}[c + d_i - (c + d_e + k_c) | c + d_i \geq b_d(d_e)] \cdot \Pr(c + d_i \geq b_d(d_e)) \\ &= \int_{d_i=\underline{d_i}}^{\overline{d_i}} \int_{c=b_d(d_e)-d_i}^{\overline{c}} (d_i - d_e - k_c) f(c) g_i(d_i) \; dc \; dd_i \\ &= \int_{d_i=\underline{d_i}}^{\overline{d_i}} (d_i - d_e - k_c) \Big(1 - F(b_d(d_e) - d_i)\Big) g_i(d_i) \; dd_i. \end{aligned} \tag{3.8}$$

Solving for the optimal bidding function requires applying the first order optimality condition to equation (3.8) given the cost distributions $F$ and $G_i$. Such a solution is trivial for some distributions (e.g., the uniform distribution), but more difficult or intractable for other distributions. Such asymmetrically-informed bidding problems have been studied in detail in common values settings (see, e.g., Wilson (1967) and Engelbrecht-Wiggans et al. (1983)). Hausch (1987) also studies the pure common values setting; he restricts the precision levels of the two suppliers' signals and finds the equilibrium bidding strategies for the first-price and second-price auctions. However, we cannot directly apply the previous equilibrium bidding results because the entrant supplier in our model the entrant has an additional known cost component. When the idiosyncratic cost is incorporated into the model, the entrant's information disadvantage can be mitigated or exacerbated by this cost asymmetry. For example, consider the case where $F$, $G_i$, and $G_e$ have support on $[0, 100]$ and $k_c = 0$. If the entrant realizes an idiosyncratic cost of $d_e = 0$, he knows that he will have a lower total cost than the incumbent with probability one. Even though he does not know the common cost component, if the entrant's bid-down-to-level is $b_d(d_e) = 0$, he wins the auction and is paid the incumbent's bid, $d_i + c$, which is greater than $d_e + c$ with probability one. In this case, the entrant bids aggressively as his bid is less than his expected cost, $\mathbb{E}[c]$.

Now consider the case where the entrant realizes an idiosyncratic cost of $d_e = 100$.

He knows that he has a higher total cost than the incumbent with probability one, and will bid down to *at least* $b_d(d_e) = 200$ (the incumbent's maximum total cost) to ensure that he does not win the auction (if he won the auction, he would make negative profit). Such a bid is conservative, as the entrant bids more than his expected cost, $100 + \mathbb{E}[c]$. We now formalize this intuition below.

**Proposition III.5.** *Suppose the entrant knows his idiosyncratic cost, $d_e$. If the entrant pays the learning fee $k_c$ to learn the common cost realization prior to the auction, the entrant's optimal bid-down-to-level is his total production cost, $b^*_{cd}(c, d_e) = c + d_e$. If the entrant does not pay the learning fee prior to the auction, the entrant's optimal bid-down-to-level, $b^*_d(d_e)$, is continuous and nondecreasing in $d_e$. Further, there exists a cost $d_e^{b-}$ such that the entrant uses a bid-down-to-level less than his expected cost if $d_e + k_c < d_e^{b-}$. Additionally, there exists a cost $d_e^{b+}$ such that the entrant uses a bid-down-to-level greater than his expected cost if $d_e + k_c > d_e^{b+}$.*

This result confirms the earlier intuition regarding the entrant's bid-down-to-level as a function of his realized idiosyncratic cost: When the entrant realizes a low idiosyncratic cost, he bids aggressively because he is fairly confident that he has a lower cost than the incumbent, and does not want to spoil his chance to win the auction by conservatively estimating the common cost. When the entrant has a high idiosyncratic cost realization, he bids himself out of the competition (i.e., bids conservatively) because he does not want to accidentally win the auction and lose money. This is in contrast to the optimal bidding strategy in the unknown idiosyncratic cost case, where the entrant's bid-down-to-level always equals his expected production cost; in the unknown common cost case, the correlation between the entrant's unknown cost and the incumbent's total cost affects the entrant's strategy.

We illustrate the entrant's optimal bidding strategy through an example in Figure 3.3, which shows the entrant's optimal bid-down-to-level as a function of his idiosyncratic cost realization, $d_e$. In this example, $F \sim$ U$[20, 80]$, $G_i$ and $G_e \sim$ U$[0, 100]$, and $k_c = 5$. When the solid line (the entrant's optimal bid-down-to-level) lies below the dotted line (the entrant's *a priori* expected cost), it is optimal for the entrant to bid aggressively, i.e., he bids down to a value less than his expected total cost. When the solid line is greater than the dotted line the entrant bids conservatively, i.e., he bids down to a value greater than his expected cost.

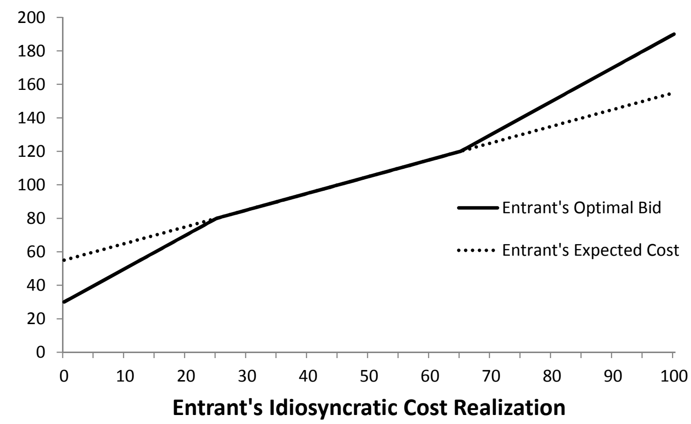



Figure 3.3: Entrant's optimal bid-down-to-level as a function of his idiosyncratic cost realization, $d_e$, when $F \sim$ U$[20, 80]$, $G_i, G_e \sim$ U$[0, 100]$, and $k_c = 5$.

### 3.5.1 Entrant's Learning Decision

The intuition behind the entrant's bidding strategy when he does not learn the common cost can also lend insight into the entrant's learning decision. When the entrant's idiosyncratic cost realization is extremely high (low), the entrant is confident that he has a higher (lower) total cost than the incumbent supplier, and thus bids with the aim to ensure that he loses (wins) the auction. In such extreme cost realization cases, the goal driving the entrant's bid is to "lock in" the outcome of the auction, resulting in the entrant losing the auction and earning zero revenue (when he has a high $d_e$) or winning the auction and being paid according to the incumbent's bid (when he has a low $d_e$). The entrant places greater value on learning the common cost prior to the auction when he is uncertain of his cost ranking relative to the incumbent — that is, when the entrant has a moderate idiosyncratic cost realization. In the following result, we show that given the entrant's realization of his idiosyncratic cost, the entrant learns $c$ if and only if the learning fee is less than a threshold learning fee.

**Proposition III.6.** *Given the entrant's realization of $d_e$, there exists a threshold $\widetilde{k}_c(d_e)$ such that the entrant learns the common cost prior to the auction if and only if $k_c \leq \widetilde{k}_c(d_e)$.*

The major distinction between this result and the analogous finding from the unknown idiosyncratic cost case stems from the dependence of the threshold on the entrant's known cost information. In both cases, the entrant makes a threshold-based decision whereby he chooses to learn if and only if the fee is less than the threshold. However, while Proposition III.2 established that the threshold learning fee is independent of the common cost realization due to the commonality of the suppliers' known costs, in this case the idiosyncratic cost realization influences the threshold.

In Figure 3.4, we consider the entrant's learning decision for the same numerical example that resulted in the optimal bidding strategy illustrated by Figure 3.3. Given the entrant's idiosyncratic cost realization, the entrant will choose to learn the common cost prior to the auction if and only if the learning fee is less than the solid line. When the entrant realizes a high idiosyncratic cost, he does not expect to have a lower total cost than the incumbent supplier. As a result, he has a low threshold learning fee because he would rather bid conservatively without learning the common cost than pay the learning fee up-front. The threshold learning fee is also low for extremely low idiosyncratic cost realizations because the entrant is confident that he has a lower total cost than the incumbent and realizes that he will be paid according to the incumbent's bid if he wins the auction. As the incumbent will incorporate the common cost into her bid of $c + d_i$, the entrant prefers to delay learning until after the auction to account for the rare possibility that the incumbent has an even lower idiosyncratic cost realization than the entrant. Finally, we note that the "hump" shape is left-skewed because the entrant is more likely to win the auction — and hence incur the learning fee regardless of his learning decision — when he has a relatively low idiosyncratic cost than if he realized a medium-to-high idiosyncratic cost.

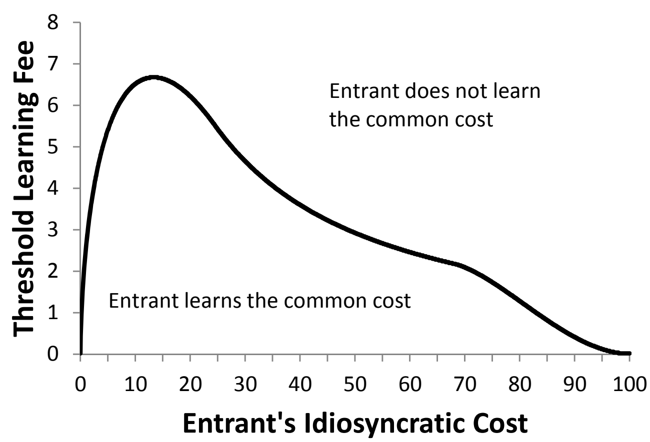



Figure 3.4: Entrant's learning decision as a function of his idiosyncratic cost realization, $d_e$, when $F \sim \mathrm{U}[20, 80]$, $G_i, G_e \sim \mathrm{U}[0, 100]$, and $k_c = 5$.

### 3.5.2 Buyer-Optimal Learning Fee

In §3.4.2, the buyer-optimal idiosyncratic learning fee is described in Proposition III.4 as the maximum between the threshold where the entrant is indifferent to learning (which does not depend on the entrant's known cost) and the point where the buyer's marginal benefit of further reducing the fee equals her cost reduction fraction. However, in this case, the buyer-optimal learning fee is not as straightforward due to the entrant's learning threshold function, which depends on the entrant's private information. Thus, the buyer-optimal learning fee must account for the entrant's learning strategy for every possible realization of $d_e$.

The buyer-optimal learning fee balances the cost reduction fraction that is incurred by the buyer, $\alpha$, with the expected changes in each entrant supplier type's bid (where a type refers to the entrant supplier's private information, $d_e$). Let the entrant's optimal bid given the learning fee and his idiosyncratic cost realization be represented as

$$b^*(k_c, d_e) = \begin{cases} b^*_{cd}(c, d_e) & \text{if} \quad k_c \leq \widetilde{k}_c(d_e) \\ b^*_d(d_e) & \text{if} \quad k_c > \widetilde{k}_c(d_e). \end{cases}$$

As the buyer will end up paying the winning supplier the drop-out bid of the losing supplier, the buyer-optimal learning fee is given by

$$k^*_c = \underset{k_c \in [0, \overline{k_c}]}{\arg\min} \left\{ \alpha(\overline{k_c} - k_c) + \mathbb{E}[\max\{c + d_i, b^*(k_c, d_e)\}] \right\}.$$

The buyer's ability to reduce the common cost learning fee bears similarities to the well-known "linkage principle" from the economics literature (see, e.g., Milgrom (2004)). The linkage principle generally states that in auctions with affiliated information, the auctioneer can maximize the expected revenue by revealing all the information she has regarding the object being sold. Thus, the procurement auction equivalent states that the auctioneer minimizes her expected cost in auctions with affiliated information by revealing as much information as possible. In short, "Honesty is the best policy" (Milgrom and Weber (1982), page 1096). We note that this is contradictory to the unknown idiosyncratic cost case, where we showed that the buyer prefers that the entrant does *not* learn the unknown cost if the learning fee is zero.

The linkage principle, however, makes an assumption that is violated by our model: The linkage principle assumes that the auctioneer does *not* incur costs to release information. In our model, the buyer is unaware of the common cost component's realization — she knows the distribution function, which is also known to both suppliers. If the buyer wants to help reveal the common cost information to the entrant supplier, she must incur an $\alpha$-fraction of the learning fee reduction. Hence, the cost benefits of reducing the learning fee must be tempered by the buyer's fee-reduction costs. Nonetheless, the linkage principle suggests that the buyer may enjoy significant savings if she reduces the fee the entrant incurs when he learns the common cost component.

For instance, consider the numerical example studied throughout this section, where $F \sim \mathrm{U}[20, 80]$ and $G_i$ and $G_e \sim \mathrm{U}[0, 100]$. The buyer-optimal learning fee is $k_c^* = 0$ for all $\alpha \in [0, 1]$ for this example; that is, the buyer will make it free for the entrant to learn the common cost, even if that requires the buyer to pay the entire default learning fee, $\overline{k_c}$. One reason why such a fee reduction is optimal surrounds the entrant's bidding strategy. Figure 3.3 depicts a wide range of idiosyncratic costs that result in the entrant bidding greater than his expected production cost. Further, if the entrant is endowed with a high idiosyncratic cost, there is a greater chance that the entrant will lose the auction and set the price that the buyer pays the incumbent. As a result, the buyer desires to lower the entrant's bid for such idiosyncratic cost realizations, and thus the buyer wants to encourage the entrant to learn prior to the auction and then bid down to his true production cost. Conversely, when the entrant has a low idiosyncratic cost and bids aggressively, the buyer does not enjoy as large of a benefit because the entrant oftentimes wins the auction, and thus the entrant's aggressive bid does not directly translate to cost savings. In general, the buyer would rather limit the entrant's conservative bids rather than encourage aggressive bidding at low cost realizations.

While the entrant will always reduce the learning fee to zero in the previous numerical example, such complete generosity is not found in all settings. Figure 3.5 considers the buyer-optimal idiosyncratic learning fee when $F \sim$ U$[45, 55]$ and $G_i$ and $G_e \sim$ U$[0, 100]$. The arrows in the figure illustrate the buyer's reduction of the learning fee for a given $\alpha$. While the buyer reduces the learning fee to zero when $\alpha \leq 0.63$, the buyer partially reduces the learning fee for higher reduction fractions if $k_c^* < \overline{k_c}$.

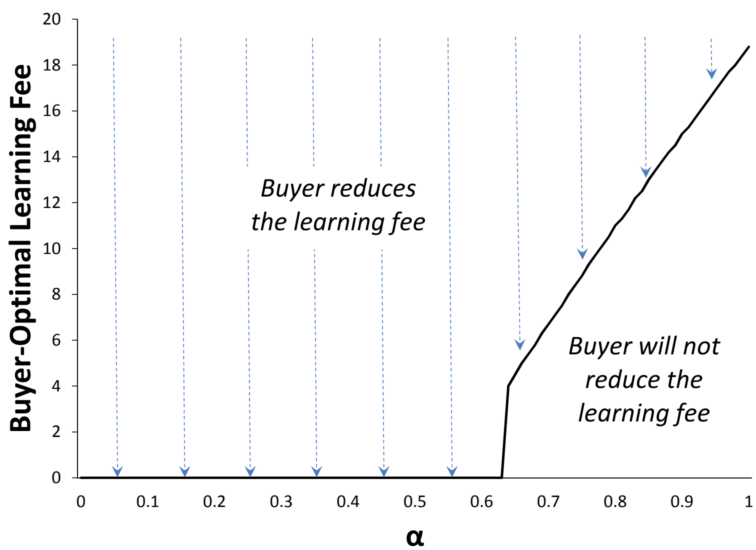



Figure 3.5: Buyer-optimal common cost learning fee as a function of the buyer-incurred cost reduction fraction, $\alpha$, when $F \sim$ U$[45, 55]$ and $G_i, G_e \sim$ U$[0, 100]$.

## 3.6 Proofs for Chapter III

### 3.6.1 Proof of Proposition III.1

When the entrant incurs the learning fee prior to the auction, he learns his total cost to supply the item, $c + d_e$. It is trivial to show that this is the optimal bid-down-to-level ($b^*_{cd}(c, d_e) = c + d_e$).

When the entrant knows $c$ but not his idiosyncratic cost, his expected profit as a function of his bid $b_c(c)$ is given by (3.2), which can be expressed as

$$\mathbb{E}[\Pi_c(b_c(c))] = \overline{G}_i(b_c(c) - c)\left[\int_{b_c(c)}^{\overline{d}_i + c} d_i \frac{g_i(d_i - c)}{\overline{G}_i(b_c(c) - c)} dd_i - c - \mathbb{E}[d_e] - k_d\right]$$

as the incumbent bids down to $c + d_i$. We want to find the entrant's expected profit-maximizing bid, so we differentiate with respect to $b_c(c)$:

$$\frac{d\mathbb{E}[\Pi_c(b_c(c))]}{db_c(c)} = g_i(b_c(c) - c)(c + \mathbb{E}[d_e] + k_d) - b_c(c) g_i(b_c(c) - c).$$

Applying the first order optimality condition results in $b^*_c(c) = c + \mathbb{E}[d_e] + k_d$.

### 3.6.2 Proof of Proposition III.2

We begin by examining how the entrant's expected profit under the two learning strategies is affected by changes in the learning cost, $k_d$. The following lemma establishes the result.

**Lemma III.7.** *The entrant's expected profit when he chooses not to learn is non-increasing convex in his learning cost, $k_d$, and the entrant's expected profit when he chooses to learn is a decreasing linear function of $k_d$.*

*Proof of Lemma III.7.* First we show that the entrant's expected profit is nonincreasing convex in the learning cost under the no-learning strategy.

$$\frac{d\mathbb{E}[\Pi_c]}{dk_d} = \frac{d}{dk_d}\left(\overline{G}_i(\mathbb{E}[d_e]+k_d)\cdot(\mathbb{E}[d_i|d_i>\mathbb{E}[d_e]+k_d]-(\mathbb{E}[d_e]+k_d))\right) \tag{3.9}$$

$$= \frac{d}{dk_d}\left(\int_{\mathbb{E}[d_e]+k_d}^{\bar{d}_i} xg_i(x)dx - (\mathbb{E}[d_e]+k_d)\overline{G}(\mathbb{E}[d_e]+k_d)\right) \tag{3.10}$$

$$= -(\mathbb{E}[d_e]+k_d)g_i(\mathbb{E}[d_e]+k_d) - \overline{G}_i(\mathbb{E}[d_e]+k_d) + (\mathbb{E}[d_e]+k_d)g_i(\mathbb{E}[d_e]+k_d) \tag{3.11}$$

$$= -\overline{G}_i(\mathbb{E}[d_e]+k_d) \leq 0 \tag{3.12}$$

and

$$\frac{d^2\mathbb{E}[\Pi_c]}{dk_d^2} = \frac{d}{dk_d}\left(-\overline{G}_i(\mathbb{E}[d_e]+k_d)\right) \tag{3.13}$$

$$= g_i(\mathbb{E}[d_e]+k_d) \geq 0. \tag{3.14}$$

The entrant's expected profit is a decreasing linear function of the learning cost under the "learn" strategy, as $\frac{d\mathbb{E}[\Pi_{cd}]}{dk_d} = -1$. □

We now establish another preliminary result.

**Lemma III.8.** *The entrant prefers to learn his cost prior to the auction if* $k_d = 0$.

*Proof of Lemma III.8.* Consider the function

$$h(d_e) = \overline{G}_i(d_e)(\mathbb{E}[d_i|d_i > d_e] - d_e) \tag{3.15}$$

which is convex as

$$\frac{d^2h(d_e)}{dd_e^2} = g_i(d_e) \geq 0. \tag{3.16}$$

By Jensen's Inequality, this implies that

$$\mathbb{E}[h(d_e)] \geq h(\mathbb{E}[d_e]). \tag{3.17}$$

We note that $\mathbb{E}[\Pi_c] = h(\mathbb{E}[d_e])$ and $\mathbb{E}[\Pi_{cd}] = \mathbb{E}[h(d_e)]$. Thus $\mathbb{E}[\Pi_{cd}] \geq \mathbb{E}[\Pi_c]$ when $k_d = 0$. $\square$

Combining Lemma III.7 and Lemma III.8, we have the result as a nonincreasing convex function and a decreasing linear function will cross once when the decreasing linear function has a larger value at the minimum possible argument of the function ($k_d = 0$) and the nonincreasing convex function is bounded below at zero.

### 3.6.3 Proof of Proposition III.3

To show both the existence of $\widehat{k_d}$ and that $\widehat{k_d} = \widetilde{k_d}$, consider the learning fee where the entrant is indifferent between learning and not learning prior to the auction (which, by definition, is $\widetilde{k_d}$). This implies

$$\begin{aligned} & \mathbb{E}[\Pi_{cd}] = \mathbb{E}[\Pi_c] \\ \implies -k_d + \int_{d_e=\underline{d}_e}^{\overline{d}_e} \int_{d_i=d_e}^{\overline{d}_i} (d_i - d_e) g_i(d_i) g_e(d_e) dd_i dd_e &= \int_{\mathbb{E}[d_e]+k_d}^{\overline{d}_i} (d_i - \mathbb{E}[d_e] - k_d) g_i(d_i) dd_i. \end{aligned} \tag{3.18}$$

Now consider the expected costs

$$\mathbb{E}[\Omega_{cd}] = \mathbb{E}[c] + \int_{d_e=\underline{d}_e}^{\overline{d}_e} \left[ \int_{d_i=\underline{d}_i}^{d_e} d_e g_i(d_i) dd_i + \int_{d_i=d_e}^{\overline{d}_i} d_i g_i(d_i) dd_i \right] g_e(d_e) dd_e + \beta(\overline{k_d} - k_d).$$

$$\mathbb{E}[\Omega_c] = \mathbb{E}[c] + \int_{d_i=\underline{d}_i}^{\mathbb{E}[d_e]+k_d} (\mathbb{E}[d_e] + k_d) g_i(d_i) dd_i + \int_{d_i=\mathbb{E}[d_e]+k_d}^{\overline{d}_i} d_i g_i(d_i) dd_i + \beta(\overline{k_d} - k_d).$$

Let the left-hand side of (3.18) be denoted by LHS and the right-hand side by RHS. Then we have

$$\mathbb{E}[\Omega_{cd}] = \mathbb{E}[c] + \text{LHS} + \int_{d_e=\underline{d}_e}^{\overline{d}_e} \int_{d_i=\underline{d}_i}^{\overline{d}_i} d_e g_i(d_i) dd_i g_e(d_e) dd_e + k_d + \beta(\overline{k_d} - k_d).$$

$$\mathbb{E}[\Omega_c] = \mathbb{E}[c] + \text{RHS} + \int_{d_i=\underline{d}_i}^{\overline{d}_i} (\mathbb{E}[d_e] + k_d) g_i(d_i) dd_i + \beta(\overline{k_d} - k_d).$$

As a result, by equation (3.18), $\mathbb{E}[\Omega_{cd}] = \mathbb{E}[\Omega_c]$, and we have that when the entrant is indifferent, the buyer is indifferent. To show that when the entrant prefers to learn (not learn), the buyer wishes that the entrant would not learn (learn), the proof is analogous – simply replace the equality in (3.18) by the appropriate inequality.

### 3.6.4 Proof of Proposition III.4

Consider how the the buyer's expected cost under each choice is affected by $k_d$:

$$\frac{d\mathbb{E}[\Omega_{cd}]}{dk_d} = -\beta \tag{3.19}$$

$$\begin{aligned} \frac{d\mathbb{E}[\Omega_{c}]}{dk_d} &= g_i(\mathbb{E}[d_e]+k_d)(\mathbb{E}[d_e]+k_d) + \int_{d_i=\underline{d}_i}^{\mathbb{E}[d_e]+k_d} g_i(d_i)dd_i \\ &\quad - g_i(\mathbb{E}[d_e]+k_d)(\mathbb{E}[d_e]+k_d) - \beta \\ &= -(\beta - G_i(\mathbb{E}[d_e]+k_d)) \end{aligned} \tag{3.20}$$

First, note that if the entrant chooses to learn his idiosyncratic cost under the default learning cost $\overline{k_d}$, the buyer will not reduce the learning cost (as her expected cost will increase and the entrant will never switch to not learning his cost prior to the auction by Proposition III.2). On the other hand, if the entrant chooses not to learn his idiosyncratic cost under $\overline{k_d}$, if $-(\beta - G_i(\mathbb{E}[d_e]+k_d))$ is positive, the buyer can reduce her expected cost by reducing the learning cost (obviously, if $\beta \geq 1$ this term cannot be positive). In this case, the optimal learning cost is the $k_d$ that solves $\beta = G_i(\mathbb{E}[d_e]+k_d)$ if the entrant does not switch to learning her cost prior to the auction at this value. If the entrant prefers to learn at a learning fee equal to $G_i^{-1}(\beta) - \mathbb{E}[d_e]$, then the buyer will reduce the cost to $\widetilde{k_d}$ (which is therefore greater than $G_i^{-1}(\beta) - \mathbb{E}[d_e]$), as the entrant will switch to learning his cost prior to the auction and any further decrease in the learning cost will result in the buyer paying a higher expected cost by equation (3.19).

### 3.6.5 Proof of Proposition III.5

The proof of $b^*_{cd}(c, d_e)$ is the same as the proof for Proposition III.1. For the case where the entrant does not learn, differentiating (3.8) with respect to $b_d(d_e)$ results in

$$\frac{d\mathbb{E}[\Pi_d(b_d(d_e))]}{db_d(d_e)} = -\int_{d_i=\underline{d_i}}^{\overline{d_i}} (d_i - d_e - k_c) f(b_d(d_e) - d_i) g_i(d_i)\ dd_i$$

where we note that $f(b_d(d_e) - d_i) = 0$ if $b_d(d_e) - d_i \notin [\underline{d_i}, \overline{d_i}]$. The optimal bid solves the first order optimality condition

$$\frac{d\mathbb{E}[\Pi_d(b_d(d_e))]}{db_d(d_e)} = 0$$
$$\implies -\int_{d_i=\underline{d_i}}^{\overline{d_i}} (d_i - d_e - k_c) f(b^*_d(d_e) - d_i) g_i(d_i)\ dd_i = 0$$

which is continuous in $d_e$ for some $b^*_d(d_e)$ as $f$ and $g_i$ are continuous (e.g., note that any $b_d(d_e)$ in $[\bar{c} + \overline{d_i}, \infty)$ is optimal when $d_e + k_c > \overline{d_i}$).

Further, $b^*_d(d_e)$ is nondecreasing in $d_e$ as the entrant's probability of winning the auction and revenue given he wins the auction is independent of $d_e$. Thus, if an entrant with idiosyncratic cost $d^1_e$ prefers $b_d$ to $b'_d$ where $b_d < b'_d$, an entrant with idiosyncratic cost $d^2_e < d^1_e$ will also prefer $b_d$ to $b'_d$ as the entrant's expected revenue will remain unchanged while the entrant's expected cost to produce the item decreases by $d^1_e - d^2_e$.

When $d_e + k_c < \underline{d_i}$, we note that the entrant will always have a smaller *ex post* production cost than the incumbent (where $k_c$ is included as a production cost because it is only incurred if the entrant wins the auction). Thus, given that the incumbent bids her cost $d_i + c \geq d_e + c + k_c$, if the buyer wins the auction he will make positive profit. As a result, it is optimal for the entrant to bid such that he wins the auction with probability one; such a bid is any $b_d(d_e) \leq \underline{d_i} + \underline{c}$. As $\underline{c} \leq \mathbb{E}[c]$, the entrant may bid less than or equal to his expected cost, $\mathbb{E}[c] + d_e + k_c$.

For $d_e + k_c > \overline{d_i}$, any auction that the entrant wins will result in him making negative profit: When the entrant wins the auction, he is paid $d_i + c$, but his cost to produce the item is $\overline{d_e} + c + k_c \geq d_i + c$. Thus, it is optimal for the entrant to bid such that he will not win the auction. The incumbent's bid is capped at $\overline{d_i} + c$, but as the entrant does not know $c$ prior to bidding, he must bid at least $\overline{d_i} + \overline{c}$ to ensure he loses the auction. For sufficiently small $k_c$, $\overline{d_i} + \overline{c} \geq d_e + \mathbb{E}[c] + k_c$ and the entrant bids greater than or equal to his expected cost; continuity results in the existence of $d_e^{b+}$.

### 3.6.6 Proof of Proposition III.6

The derivative of the entrant's expected profit when he chooses to learn prior to the auction is $\frac{d\mathbb{E}[\Pi_{cd}]}{dk_c} = -1$. The entrant's expected profit when the entrant chooses not to learn prior to the auction and bids down to the optimal level is given by equation (3.8). After applying the envelope theorem (see, e.g., Fudenberg and Tirole (1991)), we have

$$\begin{aligned}
\frac{d\mathbb{E}[\Pi_d(b_d^*(d_e))]}{dk_c} &= \frac{d}{dk_c}\int_{d_i=\underline{d_i}}^{\overline{d_i}} (d_i - d_e - k_c)\Big(1 - F(b_d^*(d_e) - d_i)\Big) g_i(d_i)\ dd_i \\
&= -\int_{d_i=\underline{d_i}}^{\overline{d_i}} \Big(1 - F(b_d^*(d_e) - d_i)\Big) g_i(d_i)\ dd_i \qquad (3.21) \\
&\geq -1 \qquad (3.22)
\end{aligned}$$

as equation (3.21) is the probability that the entrant wins the auction and thus incurs the learning fee after the auction. We note that the inequality in (3.22) will become a strict inequality for all non-trivial cases. (It will hold with equality if and only if the optimally-bidding entrant will win the auction for all incumbent idiosyncratic cost realizations; in such a case, the entrant will incur the learning fee regardless of whether he learns before or after the auction.)

Further, note that it is optimal for an entrant to learn prior to the auction if $k_c = 0$ (i.e., when learning is free) as the entrant's bid when he learns prior to the auction is the *ex post* optimal bid-down-to-level. Finally, for every $d_e$ there exists a $k_c$ such that $d_e + k_c > \overline{d_i}$; for such a $k_c$, equation (3.22) holds with a strict inequality and the entrant strictly prefers not to learn prior to the auction. In conclusion, for every $d_e$ there must exist a learning cost $\widetilde{k}_c(d_e)$ such that $\mathbb{E}[\Pi_{cd}] = \mathbb{E}[\Pi_d(b_d(d_e))]$ for $k_c = \widetilde{k}_c(d_e)$ and $\mathbb{E}[\Pi_{cd}] < \mathbb{E}[\Pi_d(b_d(d_e))]$ if and only if $k_c > \widetilde{k}_c(d_e)$.

CHAPTER IV

# Entrant Cost Uncertainty and Pre-Auction Learning: Experiments

## 4.1 Experimental Design

To study the entrant supplier's learning and bidding decisions in practice, we designed a laboratory experiment to simulate our research problem. This experimental study also aims to provide insight into the buyer's learning fee reduction strategy. If suppliers do not behave as theory predicts when they are faced with the costly opportunity to learn their cost prior to the auction, the buyer should account for this behavior when he sets the learning fee. Likewise, if entrant suppliers use a suboptimal bidding strategy, this can also affect the buyer's learning fee decision.

The experiment had two treatments: An unknown idiosyncratic cost treatment (which is analyzed in §3.4) and an unknown common cost treatment (analyzed in §3.5). The common cost distribution and both suppliers' idiosyncratic cost distribution were announced to be discrete uniform distributions on $[0, 100]$. Subjects played the role of the entrant supplier, while the computer automated the role of the incumbent supplier and subjects were aware that the incumbent bid optimally. After a sufficient introduction with comprehension quizzes and example screens, subjects were randomly matched with one of three data sets; each data set consisted of 20 known cost realizations, which were drawn randomly from the aforementioned distribution (see Table 4.1 for the three data sets). Subjects participated in 20 periods of a game where they were informed of their known cost component and then asked if they would "hire a consultant" for a given learning fee before competing against the incumbent in an auction. We used the strategy method to elicit subjects' learning decisions for four different learning fees for each known cost realization. That is, subjects were asked if they would want to hire the consultant for each learning fee, and were told that their conditional strategy would be used prior to competing with the incumbent. This method allows us to observe a subject's complete learning strategy for every known cost realization. Before making a learning decision for each learning fee, subjects had access to two decision support tools, which we will refer to as "calculators". The first calculator corresponded to the case where the entrant did not learn prior to the auction; the subject could enter a hypothetical bid and the calculator displayed the probability the subject would win the auction, the subject's expected profit if she won the auction, and the subjects' expected profit if she lost the auction for the given known cost, learning fee, and bid. The second calculator corresponded to the case where the entrant learned prior to the auction; the computer generated a random sample cost and the subject then entered a sample bid before the calculator displayed the same three quantities as in the first calculator. The subject could use the two calculators multiple times before selecting their decision.[1]

Table 4.1: Data sets of known cost realizations; each subject was randomly matched with one set.

| | | | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Set 1** | 1 | 2 | 4 | 8 | 9 | 12 | 18 | 25 | 34 | 35 | 36 | 48 | 63 | 72 | 79 | 79 | 87 | 92 | 93 | 96 |
| **Set 2** | 1 | 5 | 13 | 16 | 23 | 30 | 44 | 47 | 49 | 50 | 50 | 51 | 54 | 55 | 58 | 73 | 79 | 83 | 88 | 93 |
| **Set 3** | 4 | 4 | 5 | 15 | 20 | 24 | 25 | 32 | 49 | 51 | 58 | 59 | 60 | 62 | 66 | 68 | 74 | 74 | 92 | 96 |

[1]See Appendix A for a transcription of the written and verbal instructions given to the subjects, pictures of the screens displayed to the subjects, and comprehension quiz questions that subjects had to answer correctly before proceeding with the paid portion of the experiment.

For each known cost realization, subjects were first asked if they would hire the consultant if the fee was 1. After they entered their decision, they were asked if they would hire the consultant if the fee was 4; then 7; then 10. After entering the four decisions, the subjects faced a summary screen where they could switch any of their decisions. After the subject submitted their four decisions, the computer randomly selected one of the four learning fees and applied the subject's chosen learning decision for that fee. If the subject chose not to learn for the given learning fee, the corresponding decision support tool was available help the subject prepare her bid for the auction. If the subject instead chose to learn for the given learning fee, the computer revealed the subject's previously-unknown cost and the appropriate calculator was made available to help the subject prepare her bid. The subject then submit her bid for the auction against the optimally-bidding incumbent supplier, which was automated, and the outcome of the auction and the entrant's profit was displayed. The subject completed this process for the 20 known cost realizations from their randomly-selected data set.

The subject pool consisted of undergraduate and graduate students at the University of Michigan. Subjects were paid a $5 show-up payment plus their average profit from three randomly-selected periods, for an average total payment of $17.81 per subject. 83 subjects participated in the experiment, but five subjects' data had to be dropped from the analysis due to technical problems. Out of the 78 subjects who completed the experiment, 40 subjects participated in the unknown common cost treatement and 38 subjects participated in the unknown idiosyncratic cost treatment. An individual subject could only participate in one treatment and each session lasted approximately 75 minutes. We programmed the interface and conducted the experiment using z-Tree (Fischbacher, 2007).

We will begin by examining the subjects' learning decisions, then analyze their bidding strategies as a function of their learning decision, and finally we will consider the implications for the buyer's decision regarding reducing the learning fee.

## 4.2 The Entrant's Learning Decision

We begin by examining subjects' learning decisions. First, theory suggests that subjects should use a threshold policy for both treatments. We say that a subject uses a threshold policy if every learning fee where the subject chooses to learn prior to the auction is less than every learning fee where the subject chooses not to learn. This was indeed the case; 95% of periods in Unknown Common Treatment and 88% of periods in the Unknown Idiosyncratic Treatment contained a threshold learning policy. However, only 27% (18%) of periods in the former (latter) treatment contained a threshold policy resulted in the subject using the optimal threshold. While subjects recognize that they should use a threshold learning policy, their relative inability to select the correct threshold fee led us to study the structure of their threshold as a function of their known cost realization. In the unknown common cost case described in §3.5, we found that an optimally-behaving entrant supplier's learning decision depends on his idiosyncratic cost realization. Conversely, in the unknown idiosyncratic cost case theory states that the entrant's idiosyncratic cost learning decision is independent of his common cost realization. In Figures 4.1 and 4.2 we graph the optimal threshold (dotted line) and the entrants' average threshold (bold solid line) for the two treatments. A linear fit of the experimental data is also displayed as a thin solid line.

First, note that it appears subjects recognize that their learning threshold should depend on their idiosyncratic cost realization in Figure 4.1 and should *not* depend on

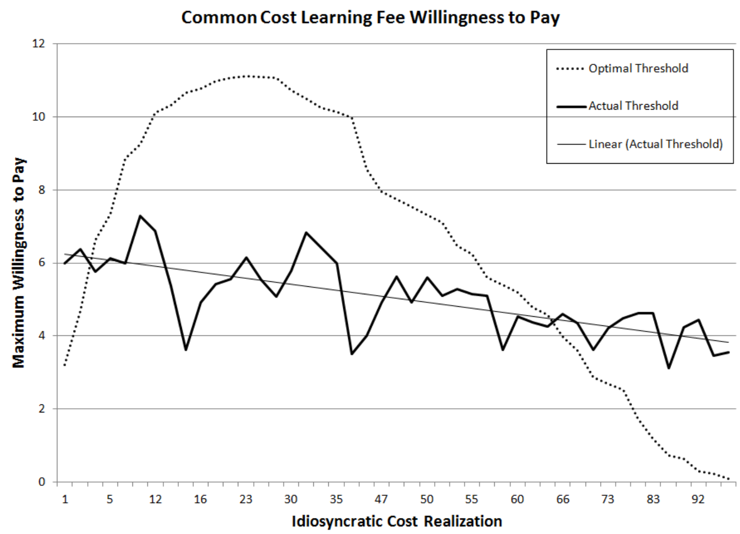



Figure 4.1: Subjects' average willingness to pay to learn prior to the auction (Unknown Common Treatment)

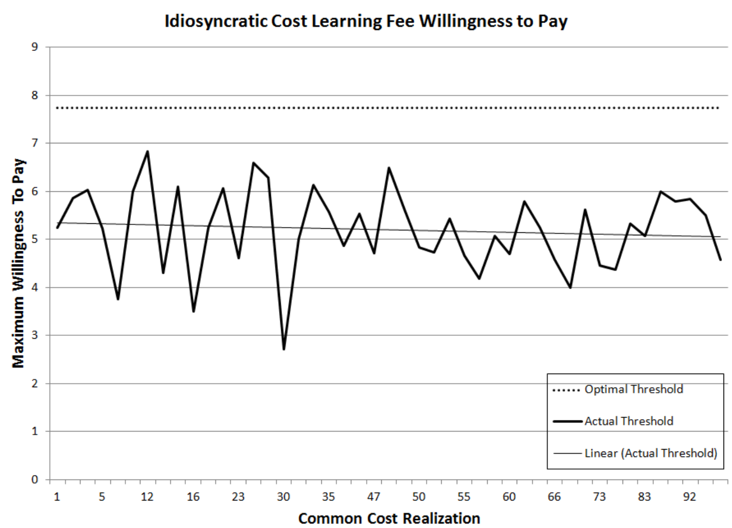



Figure 4.2: Subjects' average willingness to pay to learn prior to the auction (Unknown Idiosyncratic Treatment)

their common cost realization in Figure 4.2. To statistically test this observation, we ran eight Logit regressions with the binary learning decision as the dependent variable and the known cost realization as the independent variable. The final two columns of Table 4.2 report the results. In the Unknown Common Treatment, subjects learn significantly less often as their idiosyncratic cost realization increases for fees of

4, 7, and 10 ($p < 0.10$; we note that $p < 0.12$ for a learning fee of 1). In the Unknown Idiosyncratic Treatment, the subject's known common cost realization does not have a statistically significant influence on their learning decision for any learning fee ($p > 0.17$), which agrees with the analytical result that the entrant's learning threshold is independent of the known common cost. The "probability of learning" columns in Table 4.2 summarize the percent of periods that a subject learns prior to the auction for each learning fee as well as the theoretically-calculated fraction of periods that an entrant finds it optimal to learn. A non-parametric test for trend in learning decision across the ordered learning fees (Cuzick, 1985) confirmed that subjects learn less as the learning fee increases in each treatment (for a $p$-value of 0.01). In the Unknown Common Treatment, subjects under-learn for the lowest learning fee and over-learn for the highest learning fee, while in the other treatment subjects under-learn for fees 1, 4, and 7 and over-learn when the learning fee is 10. We note that the learning probabilities of the three smallest fees agree with the ordering of the actual and optimal thresholds in the second treatment – i.e., that the subjects have a lower than optimal threshold when they know the common cost. The tendency for subjects to under-learn confirms similar findings in the literature. Rötheli (2001) found that subjects who have the ability to learn about the prospects of two projects tend to incorrectly assess the value of information, leading to under-learning; Connolly and Thorn (1987) also found under-purchase of information in three related experiments and hypothesize that difficulty in estimating the benefit of an information source, coupled with the certainty of the information's cost, may cause this finding.

Table 4.3 shows the results of regressing the subject's average learning threshold fee on the optimal threshold fee and the known cost realization. In the unknown

Table 4.2: Entrant's probability of learning prior to the auction

| | **Probability of Learning** | | **Logit Regression** | |
|---|---|---|---|---|
| Learning Fee | Experiment | Theory | Coefficient | Standard Error |
| **Unknown Common** | | | | |
| 1 | 0.73 | 0.88 | -0.0043 | 0.0028 |
| 4 | 0.66 | 0.68 | -0.0073* | 0.0026 |
| 7 | 0.43 | 0.46 | -0.0119*** | 0.0026 |
| 10 | 0.33 | 0.23 | -0.0120*** | 0.0027 |
| **Unknown Idiosyncratic** | | | | |
| 1 | 0.77 | 1.00 | 0.0024 | 0.0030 |
| 4 | 0.68 | 1.00 | -0.0015 | 0.0027 |
| 7 | 0.47 | 1.00 | -0.0008 | 0.0025 |
| 10 | 0.31 | 0.00 | -0.0037 | 0.0027 |

For each learning fee in each treatment, the "probability of learning" represents the fraction of periods that subjects chose to learn in the experiment and the fraction of time that optimally-behaving subjects would learn. For the Logit regressions, the binary dependent variable equals 1 if the subject chose to learn in the given period and the independent variable is the subject's known cost realization. There were 800 and 760 observations for each learning fee in the Unknown Common and Unknown Idiosyncratic treatments, respectively. Significance is denoted: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

common cost case given by column (1), the average subject learning threshold is decreasing in their realized idiosyncratic cost ($p < 0.01$); the average threshold is too high for extremely low and high idiosyncratic cost realizations, and too low for low-to-medium realizations. This evidences that subjects understand the general intuition of the Unknown Common Treatment, but moderate their changes to their threshold learning fee. Further, subjects fail to comprehend the nuance behind having a low threshold for extremely low cost realizations; however, such a mistake is minor and requires a deep understanding of the benefits of using a low threshold for such realizations (namely, that the entrant can bid aggressively and save the learning fee in the unlikely case that the incumbent has an extremely low cost). Confirming the result from the Logit regressions, the subjects also recognize that their learning threshold should be constant in their cost realization in the Unknown Idiosyncratic Treatment (column (2))[2]; however, their average threshold is 34% lower than the optimal threshold.[3] We note that the constant term in the regression is omitted because the optimal learning threshold is a constant (equal to 7.74 for all common cost realizations).

[2] $p > 0.6$ for the known cost realization coefficient from Table 4.3

[3] This 34% difference is significant for a $p$-value of 0.01.

Table 4.3: Regression of actual learning threshold on optimal learning threshold and known cost

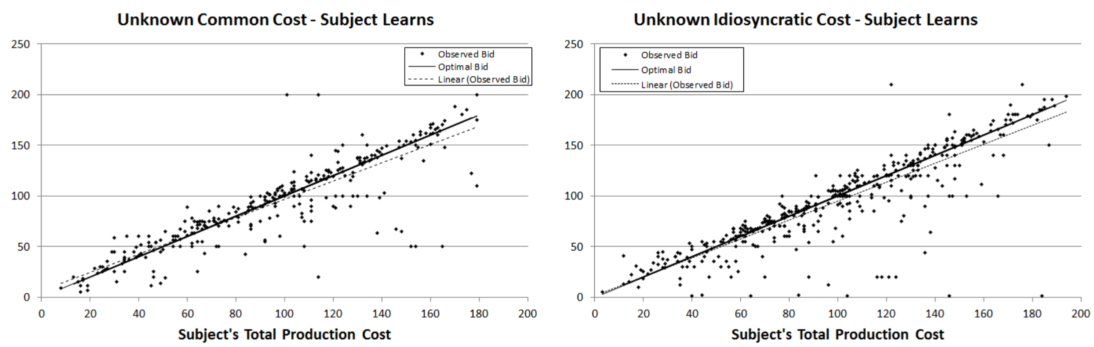
| Coefficients | (1) Unknown Common Treatment | (2) Unknown Idiosyncratic Treatment |
|---|---|---|
| Optimal Learning Threshold | -0.000063 | 0.677*** |
| | (0.0473) | (0.0651) |
| Known Cost Realization | -0.0242*** | -0.00299 |
| | (0.00814) | (0.00577) |
| Constant | 6.14*** | |
| | (0.733) | |
| Observations | 3,032 | 2,672 |
| Number of Subjects | 40 | 38 |

Robust standard errors clustered at the subject level reported in parentheses. Significance is denoted: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The dependent variable is the subjects' actual learning threshold (i.e., the learning fee where the subject switches from learning to not learning prior to bidding). The first column corresponds to the Unknown Common Treatment and the second column to the Unknown Idiosyncratic Treatment. The constant term is omitted from column (2) as the optimal learning threshold is a constant. The specification is GLS with subject random effects, and the observations are restricted to periods where the subject used a threshold learning policy.

## 4.3 The Entrant's Bidding Strategy

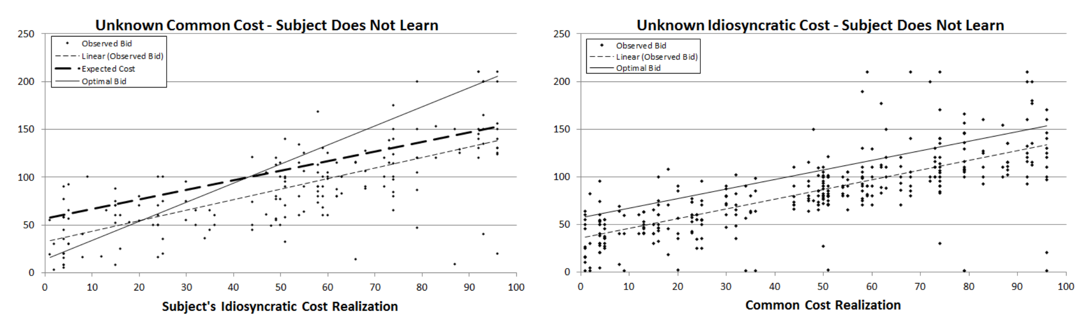
While the first part of our experiment investigated the subjects' learning decisions, the second half of the game tested the subjects' bidding strategies given their stated learning decision. While the subject made four learning decisions for each period of the game, only one learning decision was implemented due to use of the strategy method. Thus, each subject generated 20 bids (1 per period), and the distribution of bids made after the subject learned their unknown cost approximately followed the distribution from §4.2. Figures 4.3(a) and 4.3(b) show the subjects' bids when they choose to learn the unknown cost prior to bidding. When the entrant learns prior to the auction, he has a weakly dominant strategy to bid his true production cost of $c + d_e$; in both treatments, subjects recognize the optimality of this strategy and bid equal to their cost.

Intuitively, it is more difficult for a subject to determine the optimal bid when the subject does not learn the unknown cost prior to the auction. Figures 4.4(a) and 4.4(b) graph the subjects' bids for this case. One can immediately notice that subjects' bids are more variable than the bids from the case where the entrant learns prior to bidding. In the Unknown Common Treatment, the dotted line represents the entrant's expected cost given the subject's idiosyncratic cost realization, while the solid line represents the subject's optimal bid. The difference between the expected cost and optimal bid supports the result of Proposition III.5; the optimally-behaving entrant should bid much lower (higher) than his expected cost when he realizes a low (high) idiosyncratic cost. In the Unknown Idiosyncratic Treatment, the subject's optimal bid is equal to his expected cost given the common cost realization. While the subjects' bids are more variable than in the case where the subjects learn, they appear to correlate with the subject's expected cost minus a constant term.




(a) Unknown Common Treatment. (b) Unknown Idiosyncratic Treatment.

Figure 4.3: Bidding strategies when the subjects learn the unknown cost prior to bidding.




(a) Unknown Common Treatment. (b) Unknown Idiosyncratic Treatment.

Figure 4.4: Bidding strategies when the subjects do not learn the unknown cost prior to bidding.

To further study the subjects' bids, we regressed their bids on the subjects' learning decision and expected cost given the cost information the subject has prior to bidding.[4] The results of the regression are summarized in Table 4.4.

Table 4.4: Effect of learning decision and entrant's expected cost after making the learning decision on the entrant's bid

| Coefficients | (1) Unknown Common Treatment | (2) Unknown Idiosyncratic Treatment |
|---|---|---|
| Learn Prior to Bidding | 39.1*** | 20.9*** |
| | (8.14) | (5.37) |
| Expected Cost Prior to Bidding | 1.11*** | 1.02*** |
| | (0.0729) | (0.0631) |
| Learn & Expected Cost Prior to Bidding | -0.200*** | -0.102 |
| | (0.0685) | (0.0689) |
| Constant | -36.0*** | -20.4*** |
| | (8.10) | (5.84) |
| Observations | 800 | 760 |
| Number of Subjects | 40 | 38 |

Robust standard errors clustered at the subject level reported in parentheses. Significance is denoted: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The dependent variable is the subjects' bid. The first column corresponds to the Unknown Common Treatment and the second column to the Unknown Idiosyncratic Treatment. The specification is GLS with subject random effects.

In both treatments, the regressions' constant terms imply that subjects bid significantly less than their expected cost when they do not learn prior to the auction ($p < 0.01$). This is in agreement with the literature (e.g., Kagel et al. (1987)), which has found that subjects tend to bid aggressively in second price auctions with unknown information. For example, Cooper and Fang (2008) study second-price private value (forward) auctions and find that subjects overbid; they find support for both a 'joy of winning' hypothesis and a 'spite' hypothesis. Such aggression is a benefit to the buyer in our model, as the aggressive bidding results in lower expected costs. When the subjects learn prior to the auction, the "learn prior to bidding" coefficients essentially cancel the constant terms in both treatments, and the subjects bid equal to their expected cost.

When subjects do not learn before bidding, their bid increases one-for-one with

[4] If the subject learns prior to bidding, the subject's cost is known ($c + d_e$). If the subject does not learn, the subject's expected cost is the known cost plus the expectation of the unknown cost plus the learning fee (because the entrant will have to pay the learning fee if he wins the auction).

expected cost in both treatments (a Wald test (Harrell, 2001) for the coefficient on Expected Cost being equal to one finds $p > 0.10$ in both treatments). When subjects learn their unknown cost prior to bidding they also increase their bid close to one-for-one with cost (albeit slightly but significantly slower, $p < 0.05$ for both treatments). For the case where the subject's optimal bid does *not* equal his expected cost (i.e., the case where he does not learn when he does not know the common cost), we also regressed the subjects' bids on the optimal bid; however, we found that the subjects' expected cost was a much better predictor of the subjects' bids. While theory predicts that the amount an entrant's bid varies from his expected cost should depend on the idiosyncratic cost realization, we could not find this to be statistically significant. A similar result was also shown in Eyster and Rabin (2005), which argued that a "cursed equilibrium" (where a subject underestimates the correlation among bidders' information) in the context of a second price auction would result in the subject bidding closer to his *ex ante* expected cost instead of the optimal bid. The subjects' bidding when they do not learn the common cost carries additional considerations for the buyer. As the subject bids approximately equal to their expected cost minus a constant, this results in the entrant's bid having a larger deviation from the optimal bid at certain idiosyncratic cost realizations. Namely, compared to the optimal bid subjects tend to bid too high at low idiosyncratic cost realizations and too low at high costs. From the buyer's perspective, a lower-than-optimal bid (at high cost realizations) is a welcomed strategy: a lower bid results in reduced procurement costs. Conversely, the conservative bids at low cost realizations inflate the buyer's costs. In the next subsection, we further investigate how the buyer's costs are affected by the subjects' learning and bidding decisions.

## 4.4 Implications for the Buyer's Fee Reduction Decision

This experiment was designed to directly measure entrant subjects' learning decisions and bidding strategies. However, an equally important question surrounds the buyer's procurement costs and choice of learning fee, which is set at the outset of the sourcing mechanism. In §3.4.2 and §3.5.2 we found that, in theory, reducing the learning fee can have a significant effect on the buyer's cost; not only can the buyer influence the entrant's learning decision by reducing the fee, but she can also influence the entrant's bid when he chooses not to learn. However, the magnitude of these savings depends on the entrants' subsequent learning and bidding decisions.

We previously established that subjects tend to under-learn (e.g., in aggregate subjects have a lower threshold learning fee than the optimal threshold) and bid suboptimally when they do not learn their unknown cost. Given the data generated by our experiment, we now investigate the effects of these suboptimal decisions on the buyer's strategy. Table 4.5 summarizes the buyer's average experimental and theoretical cost as a function of the learning fee, where the buyer's cost is the maximum of the entrant's and the incumbent's bids. Theory predicts that the buyer can enjoy significant savings[5] from reducing the learning fee in the unknown common cost case. However, such savings are not apparent in the experiment: Reducing the learning fee by one step[6] does not result in a statistically significant reduction in the buyer's cost.[7]

In the unknown idiosyncratic cost case, the buyer's theoretical expected cost is equal for learning fees 1, 4, and 7 because the entrant supplier will learn for all learn-

[5]Note that the theoretical cost values in Table 4.5 are theoretical calculations, and thus are statistically distinct.

[6]A "step" refers to the buyer reducing the learning fee to the next-smallest value (i.e., from a fee of 10 to a fee of 7).

[7]A Wilcoxon rank-sum test (Wilcoxon, 1945) of the buyer's average cost differences between each step in learning fees all result in $p > 0.10$ for both treatments (even for the 5.1 unit decrease in average cost obtained from reducing the fee from 10 to 7 in the Unknown Common Treatment). This is also evident from the 95% confidence intervals in Table 4.5.

Table 4.5: Buyer's average costs for each learning fee.

| **Learning Fee** | **Buyer's Average Cost** | **95% Confidence Interval** | **Theoretical Cost** |
|---|---|---|---|
| **Unknown Common** | | | |
| 1 | 116.7 | [111.5, 121.9] | 123.8 |
| 4 | 114.9 | [109.7, 120.1] | 130.6 |
| 7 | 114.5 | [108.9, 120.0] | 135.3 |
| 10 | 119.6 | [114.2, 124.9] | 139.8 |
| **Unknown Idiosyncratic** | | | |
| 1 | 108.7 | [103.2, 114.3] | 116.7 |
| 4 | 111.2 | [105.4, 117.1] | 116.7 |
| 7 | 109.5 | [103.6, 115.4] | 116.7 |
| 10 | 113.0 | [107.9, 118.1] | 118.0 |

The buyer's average cost for the given learning fee is the average of the price the buyer would pay for the contract in a given period (i.e., the maximum of the subject's bid and the automated incumbent's bid). The theoretical cost for a given learning fee is the average price the buyer would pay for the contract in a given period if the subject made the optimal learning decision and then bid optimally (where it is assumed that the actual unknown cost for the given period is revealed to the optimally-bidding entrant if the entrant learns).

ing fees less than 7.74, regardless of his common cost realization. These theoretical costs confirm our finding from §3.4, which stated that if the learning fee reduction fraction is small enough, the buyer will find it optimal to reduce the learning fee until the entrant is indifferent to learning before the auction. In our experiment, however, reducing the learning fee was not statistically shown to reduce the buyer's costs ($p > 0.10$).

To further explore why the buyer does not expect to benefit from changes in the learning fee in our experiment, Table 4.6 breaks down the buyer's marginal benefit of reducing the fee by the learning decisions that subjects chose at each fee.[8] The marginal benefit for each pair of learning decisions represents the reduction in the buyer's average cost; for each learning fee that was randomly selected for the auction, the respective subject's learning decision for the higher of the two fees and the buyer's cost in the auction were recorded. That subject's learning decision at the lower fee was then retroactively applied and a bid based on the subjects' empirical distribution was used to calculate the change in the buyer's cost.[9]

[8]We restricted the data for this table to periods that contained a threshold learning decision (95% and 88% of periods in the two treatments, respectively) due to the focus on the marginal benefit generated by the subject switching from not learning at the higher fee to learning at the reduced fee.

[9]In the case of "L→L", the subject was assumed to bid the same value when the learning fee was reduced as subjects bid statistically equal to $c + d_e$ when they knew both costs. For "N→N", the subject's bid was decreased according to the fee reduction (3) times the slope coefficient from the regressions in Table 4.4. For "N→L", the

Table 4.6: Buyer's marginal benefit of reducing the learning fee.

| **Learning Fee Reduction** | **Buyer's Marginal Benefit** Overall | L→L | N→N | N→L | **Pr(Outcome)** L→L | N→N | N→L |
|---|---|---|---|---|---|---|---|
| **Unknown Common** | | | | | | | |
| 10 → 7 | 0.5 | 0.0 | 1.2 | -3.1 | 0.66 | 0.24 | 0.09 |
| 7 → 4 | -2.0 | 0.0 | 1.2 | -8.5 | 0.43 | 0.29 | 0.28 |
| 4 → 1 | 0.3 | 0.0 | 1.3 | -0.7 | 0.28 | 0.62 | 0.10 |
| **Unknown Idiosyncratic** | | | | | | | |
| 10 → 7 | -0.5 | 0.0 | 1.3 | -6.4 | 0.69 | 0.19 | 0.12 |
| 7 → 4 | -0.1 | 0.0 | 1.3 | -1.8 | 0.45 | 0.29 | 0.26 |
| 4 → 1 | -0.6 | 0.0 | 0.5 | -5.4 | 0.30 | 0.51 | 0.19 |

The notation "10 → 7" and "N→L" refers to the buyer reducing the learning fee from 10 to 7 and the subject *not learning* prior to the auction when the fee is 10 and *learning* for a fee of 7, respectively. The buyer's marginal benefit numbers are the decrease in the buyer's average cost and the "Pr(Outcome)" gives the fraction of periods where the subject would make the given learning decisions at the respective learning fees.

First, we note that the buyer does not benefit if the subject learns under both fees; under either fee, the subject will bid equal to his production cost $c + d_e$, so the auction's outcome and buyer's payment will not change. Second, if the subject does not learn under both fees, the buyer's auction payment is expected to decrease by approximately 1.2 (depending on the level of the fees). We found in §4.3 that subjects' bids correlated closely with their expected cost when they did not learn, so the buyer can expect to save an amount approximately equal to the fee reduction *when the entrant sets the price of the auction* (i.e., loses the auction). The buyer can expect the entrant to set the price of the auction about half of the time; such a "sanity check" confirms the relative size of the buyer's marginal benefit when the subject does not learn under both fees.[10] Finally, when the subject switches from not learning at the higher learning fee to learning at the reduced fee, the buyer's cost is expected to increase. This is a consequence of the subjects' bidding strategies: In the Unknown Idiosyncratic Treatment, the average subject bids 34% lower than the optimal bid (which is equal to the subjects' expected cost). This aggressive bidding

buyer's newly-learned production cost, $c + d_e$, was used. The "L→N" case does not apply due to the restriction to threshold learning strategies.

[10] Such a calculation ignores the interaction between the entrant's known cost and learning decision for the given fee — in the Unknown Common Treatment, subjects who do not learn for a given fee are more likely to have a higher known cost realization than those who learn, which in turn affects the probability the entrant will set the price — but we believe our explanation most clearly communicates the intuition for this case.

behavior benefits the buyer. However, when the subject learns at the reduced fee, the subject bids equal to his cost, $c + d_e$. Thus, by reducing the learning fee the buyer loses the subjects' aggressive bidding tendencies and pays a higher expected cost. This effect is also evident in the Unknown Common Treatment. However, we remind the reader that in this treatment subjects were shown to bid equal to their expected cost minus a constant, which had a flatter slope than the entrant's optimal bidding strategy. This results in the subject bidding aggressively with respect to the optimal bid at high idiosyncratic cost realizations — which benefits the buyer — and conservatively with respect to the optimal bid at low idiosyncratic cost realizations — which raises the buyer's costs. As the subjects' bids only affect the buyer's cost when the subject loses the auction, the benefit of the subjects' aggressive bidding behavior at high cost realizations outweighs the effect of higher subject bids at low cost realizations.

In summary we find that theory suggests that the buyer may be able to save money by reducing the learning fee, but in our experiment the costly reduction of the learning fee does not have a statistical impact on the buyer's costs! The primary driver of this result is an entrant's aggressive bidding strategy when he does not learn prior to bidding. This suggests that buyers may be able to save time, money, and resources that they otherwise would devote to going "above-and-beyond" in helping their potential suppliers compete against other suppliers.

## 4.5 Conclusions from Theoretical and Experimental Results

In practice, entrant suppliers looking to enter a buyer's supply base may be initially uncertain of their costs to produce the good or service up for bid to the buyer's specifications. Such cost ambiguity can stem from a variety of sources — the entrant may need to pinpoint the amount of materials needed to make the good or the licenses and regulations that need to be obtained (which can be classified as common costs that all suppliers must incur) or determine the labor time and yield rate associated with their manufacturing process (a supplier-specific cost). While such a situation is relatively common among suppliers looking to do business with new buyers, both the theoretical and experimental operations literature fail to address our model's setting: First, we analyze the entrant's decision of whether to pay a learning fee to resolve his cost uncertainty after finding his bidding strategies. Additionally, we consider the buyer's option to reduce the learning fee by expending her own costly effort. We find theoretical results and perform an experiment to elicit subjects' learning and bidding decisions to determine if the buyer's learning fee reduction strategy should be altered from the theoretically-prescribed strategy. To our knowledge, this is the first experimental research problem to examine costly learning decisions in an auction setting.

We find that an entrant supplier should utilize a threshold learning policy, whereby the entrant learns the total cost to supply the buyer if the learning fee is less than the threshold. In the case where the unknown cost information is a supplier-specific cost, this threshold is independent of the known common cost; however, when the common cost is unknown the entrant's threshold is greater for medium idiosyncratic costs — where the entrant is likely to be competitive with the incumbent — and smaller for extreme cost realizations due to the buyer's relative certainty of his cost ranking with respect to the incumbent supplier. The experiment confirmed that subjects recognized the optimality of a threshold learning strategy, but tended to use too low of a threshold for the majority of cost realizations. Further, subjects recognized that their threshold learning fee should not depend on their cost realization when the known cost is a commonly-shared cost, but should depend on their supplier-specific idiosyncratic cost realization. However, they did not fully capture the nuances behind the threshold in the latter case, instead using a threshold that decreased in their idiosyncratic cost.

Subjects adhered to the weakly-dominant strategy of bidding equal to their total cost when they chose to learn their unknown cost information prior to the auction. When subjects did not learn their unknown cost, they bid according to their *expected* cost minus a constant term; this aggressive bidding resulted in the buyer saving procurement costs. While such a bidding strategy correlates well with the optimal bid in the unknown idiosyncratic cost case, this strategy diverges from the entrant's optimal bid for the other treatment. In the unknown common cost case, theory predicts that an entrant should bid less than his expected cost for low idiosyncratic costs to ensure that he wins the auction, and should "price himself out" of auctions where his idiosyncratic cost is high by bidding greater than his expected cost. Instead, the subjects' empirically-described strategy results in higher than optimal bids at low costs and lower than optimal bids at high realizations.

Subjects' threshold learning policy — which results in the entrants learning less often than theory prescribes — and tendency to bid aggressively (i.e., less than their expected cost) when they do not learn prior to the auction carries important implications for the buyer's choice of learning fee. In §3.4.2, theory states that a buyer should reduce the learning fee to the point where the entrant is indifferent to learning prior to the auction (if the buyer's cost reduction fraction is sufficiently small). The buyer-optimal learning fee is more complicated when the entrant does not know the common cost; §3.5.2 explains how the buyer must account for the change in learning strategies and bids for every supplier type when determining the optimal learning fee. However, the subjects' tendency to under-learn and then bid too aggressively when they do not learn prior to the auction results in the buyer realizing virtually zero cost savings when she reduces the learning fees! While practitioners still must ensure that their RFQ's and information made available to potential suppliers is sufficient, our experiment finds that the buyer need not take great pains to make it as easy as possible for suppliers to learn their total cost to produce the buyer's item prior to the competitive sourcing event.

## CHAPTER V

# Conclusion

Sourcing has recently emerged as an important research topic in operations and supply chain management; the relative novelty of the field has left many practical questions unanswered by the current literature. This dissertation aims to address issues for buyers and suppliers when the supply base consists of both incumbent and entrant suppliers.

In Chapter II, the pool of incumbent suppliers are at-the-ready to bid for a multi-unit contract. Meanwhile, the buyer may want to perform a costly supplier recruitment round, where she discovers and recruits entrant suppliers to join her supplier pool. We develop a novel "test auction" sourcing technique, where the buyer may hold an auction among the incumbent suppliers for a small quantity of the item before she decides how many entrant suppliers to recruit, and analyze the test strategy when the buyer can also use a reserve price. Comparative statics results provide a guide for determining when the test auction strategy is most beneficial in practice. We numerically compare the test with reserve price strategy to the optimal mechanism, and find that the test with reserve price strategy performs well considering its ease of implementation. Finally, we address two different extensions to the model: First, we discuss intractability issues when the buyer uses a first-price sealed-bid auction instead of the modeled second-price open-bid auction; regardless of these issues, we extend the comparative statics results to the sealed-bid first-price and the reverse Dutch auction formats. Second, we allow the buyer to update her belief on the entrant suppliers' cost distribution based on the incumbent suppliers' bid-down-to levels in the first test auction and show that related forms of the comparative statics results hold when the buyer only allows the incumbent supplier who is awarded units in the first test auction to compete with entrant suppliers in future auctions.

In Chapter III, we study an entrant supplier who competes against an incumbent supplier for a contract while facing a cost information disadvantage. It is natural for an incumbent supplier — who has previously produced the good or service (or a previous generation of the good) for the buyer — to be more informed regarding her costs of fulfilling the contract than an entrant supplier, who has not had experience with the particular good or service that the buyer is procuring. We distinguish between which type of cost is unknown to the entrant supplier: First we study the case of an unknown idiosyncratic cost component and then we study the unknown common cost component case. We discuss the differences in the entrant's learning and bidding strategies and the buyer-optimal learning fee reduction amounts between the two cases.

While the entrant's bidding strategy is straightforward when he decides to learn prior to bidding, this is not the case when he has an unknown common cost component — we find that the entrant bids "aggressively" (less than his expected production cost) when he realizes a low idiosyncratic cost and "conservatively" (greater than his expected production cost) when he realizes a high idiosyncratic cost. Conversely, when the entrant's idiosyncratic cost is unknown, his optimal bidding strategy does not deviate from his expected production cost. We find that the entrant's choice of whether to resolve his cost uncertainty prior to bidding depends on his idiosyncratic cost realization but *not* on his common cost realization. Finally, we find that the buyer-optimal learning fee — that is, a proxy for the amount of "help" the buyer gives the entrant — is a simple calculation in the unknown idiosyncratic cost case as the buyer is able to predict the entrant's learning decision based solely on the learning fee; the buyer will reduce the entrant's learning fee until the entrant is indifferent between learning and not learning unless the buyer's cost of fee reduction is too expensive. However, the buyer's choice of learning fee is much more complex in the unknown common cost case as the entrant's learning decision depends on his private information.

Finally, in Chapter IV we study the research problem from Chapter III in a controlled laboratory experiment with undergraduate and graduate students from the University of Michigan. Subjects recognized the optimality of a threshold learning strategy, but used too low of a threshold for the majority of cost realizations. Further, subjects recognized that their learning strategy should not depend on their cost realization when the known cost is a commonly-shared cost, but should depend on their supplier-specific idiosyncratic cost realization. However, they did not capture the nuances behind the threshold in the latter case, instead using a threshold that decreased in their idiosyncratic cost. Subjects adhered to the weakly-dominant strategy of bidding equal to their total cost when they chose to learn their unknown cost information prior to the auction. When subjects did not learn their unknown cost, they bid according to their *expected cost* minus a constant term; this aggressive bidding behavior resulted in the buyer saving procurement costs. While such a bidding strategy correlates well with the optimal bid in the unknown idiosyncratic cost case, this strategy diverges from the entrant's optimal bid for the other treatment.

Finally, the subjects' tendency to under-learn and then bid too aggressively when they do not learn prior to the auction results in the buyer realizing virtually zero cost savings when she reduces the learning fees from the highest fee studied in the experiment; this finding was not predicted by theory.

In conclusion, the operations management literature often assumes that suppliers are *ex ante* identical, and hence does not fully address some practical considerations in many sourcing situations. We address two specific issues when a buyer's potential supplier pool consists of incumbent and entrant suppliers: How a buyer can best structure the sourcing process when potential supplier recruitment is costly, and a buyer's and entrant supplier's optimal actions when the entrant must pay a learning fee to realize his total cost. We hope that the insights derived throughout this dissertation provide guidance to academics and practitioners alike.

# APPENDIX

# APPENDIX A

# Appendix for Chapter IV: Entrant Cost Uncertainty and Pre-Auction Learning: Experiments

The following is a transcription of the unknown common cost treatment's instructions for the experiment described in Chapter IV (the instructions for the unknown idiosyncratic cost treatment are analogous). Section A.1 covers the written instructions that are displayed to subjects via the z-Tree interface. Section A.2 transcribes the quiz questions that subjects must answer to confirm that they comprehend the instructions before proceeding to the game. Finally, §A.3 contains screenshots of the z-Tree interface and verbal instructions that are read by the experiment's facilitator.

## A.1 Written Instructions for the Unknown Common Cost Treatment

Welcome to today's session and thank you for coming! At this point, please do not talk to any other participant, or look at their computer. If you have any questions, raise your hand and somebody will come help you individually. We are studying individual decision-making when subjects have the opportunity to learn information. You will play 20 periods of a game. At the end of the experiment, you will be paid the $5 show up fee plus your earnings from the experiment.

In this game, an incumbent supplier and an entrant supplier are competing to supply a buyer with an item. An "incumbent supplier" is a supplier who has been making the item for a while. An "entrant supplier" is a new supplier who is trying to enter the market – unlike the incumbent supplier, they have not made the item for the buyer in the past. The entrant is competing with the incumbent for the buyer's business. You will be the ENTRANT supplier, and the computer will be the incumbent supplier. Both suppliers will submit bids to the buyer, and the buyer will award the contract to the supplier who bids the lowest. The winning supplier (i.e., the supplier who bids the lowest) will be paid the losing supplier's bid (i.e., the larger of the two bids). For example, if the incumbent (computer) bids \$120 and the entrant (you) bids \$90, the entrant (you) will be awarded the contract and you will be paid \$120 to supply the item.

Of course, it costs money for the suppliers to build the item. For each supplier, their cost is the sum of two costs:

1) PRODUCTION COST (labor, machining, etc.), which is different for each supplier

2) REGULATORY COST (governmental fees, etc.), which is the same for each supplier.

Thus, each supplier's total cost to make the item is given by

Incumbent's Cost = Incumbent's Production Cost + Common Regulatory Cost

Entrant's Cost = Entrant's Production Cost + Common Regulatory Cost

Suppose the incumbent's (computer's) production cost is 25, the entrant's (your) production cost is 40, and the regulatory cost is 60. Then each supplier's cost to make the item is:

Incumbent's Cost $= 25 + 60 = 85$

Entrant's Cost $= 40 + 60 = 100$

Both suppliers know their own production cost but not their opponent's. All they know about their opponent's production cost is that it is a whole number between 0 and 100, with each number being equally likely. For example, you may know that your production cost is 39, but all you know about the incumbent's production cost is that it is between 0 and 100 (with each number equally likely). Similarly, the incumbent knows her own production cost but does not know your production cost.

The regulatory cost is EQUAL for both suppliers. The incumbent supplier knows the regulatory cost because she has produced a similar item in the past. The entrant supplier (you) does NOT know the regulatory cost. You do know that the regulatory cost is a whole number between 0 and 100, with each number being equally likely. The incumbent is aware that you know this range of costs. The regulatory cost and your production cost are independent of each other (if the production cost is high that doesn't necessarily mean the regulatory cost is high or low).

To make the item, you need to LEARN the regulatory cost. To learn the regulatory cost, you must hire a consultant and pay a "consultant fee". If you pay the consultant fee, the consultant will research the necessary regulations and reveal the regulatory cost. You can DECIDE to pay the consultant fee up-front so you learn the regulatory cost before submitting your bid. You don't have to hire the consultant before the auction, though; instead, you could bid WITHOUT learning the regulatory cost. If you then *WIN* the auction, you'd have to pay the consultant fee in order to examine the regulatory process and learn the regulatory cost of making the item. On the other hand, if you *LOSE* the auction, you don't have to pay the consultant fee.

**Your Decision: Hire the consultant before or after bidding?** In summary, at the beginning of the game you have 2 options:

A) Pay the consultant fee and learn the regulatory cost BEFORE submitting your bid to the buyer, or

B) Submit your bid without learning the regulatory cost. In this case, if you win the auction you must then pay the consultant fee to learn the regulatory cost in order to make the item. If you lose the auction, you do not need to pay the consultant fee.

**Main Trade-Off:** Under A), you know your total cost before submitting a bid, but you had to pay the consultant fee up-front. Under B), you know your production cost but you don't know the regulatory cost when you submit a bid, but if you end up losing the auction you don't have to pay the consultant fee.

**The Incumbent's Bid:** As previously described, the incumbent supplier (computer) already knows her own production cost as well as the regulatory cost (which is the same for both you and the incumbent). Thus, the incumbent does NOT have to learn the regulatory cost, and therefore does not have to pay the consultant fee. For this experiment, the incumbent (computer) will ALWAYS bid equal to her total cost (production cost + regulatory cost). For example, if the incumbent's production cost is 12 and the regulatory cost is 60, the incumbent (computer) will bid 72.

Your monetary payoff depends on **your profit** from randomly-selected periods of the game. <u>**Your Profit = Your Revenue - Your Costs**</u>.

<u>Your Revenue = What the buyer pays you.</u> If you *win* the auction, the buyer pays you the incumbent's bid (which is the highest bid). If you *lose* the auction, the buyer does not pay you anything (the buyer will pay the incumbent instead).

<u>Your Costs = What you actually pay.</u> If you *win* the auction, you must make the item, and thus you will pay three costs: the consultant fee (which you may have paid prior to bidding), the regulatory cost, and your production cost. If you *lose* the auction, you do NOT make the item. As a result, you do not pay the regulatory cost or your production cost. HOWEVER, if you hired the consultant to learn the regulatory cost prior to bidding, you already paid the consultant fee.

## A.2 Comprehension Questions

### A.2.1 Comprehension Quiz 1

Suppose your production cost is 20 and the consultant fee is 7. You don't know the incumbent's production cost, and at this point you have to decide whether to pay the consultant fee to learn the regulatory cost before you bid, or bid without learning. Imagine that you pay the consultant fee and learn that the regulatory cost (which is the same for both you and the incumbent) is 45. Now you have to submit a bid to the buyer. You bid 70. After the incumbent also submits a bid, it is revealed that the incumbent bid 87.

**Question 1a:** Which supplier gets to make the item for the buyer (i.e., wins the auction)? (Answer: Entrant)

**Question 1b:** How much does the buyer pay you to make the item (your revenue)? (87)

**Question 1c:** What is your total cost to supply the item (including the consultant fee)? (72)

**Question 1d:** What is your profit? (15)

### A.2.2 Comprehension Quiz 2

We consider the previous example except we change the incumbent's bid to 60.

**Question 2a:** Which supplier gets to make the item for the buyer (i.e., wins the auction)? (Incumbent)

**Question 2b:** How much does the buyer pay the incumbent to make the item? (70)

**Question 2c:** How much does the buyer pay you in this example (your revenue)? (0)

**Question 2d:** What is the total cost that you incurred in this example? (7)

**Question 2e:** What is your profit? (-7)

#### A.2.3 Comprehension Quiz 3

Now suppose your production cost is 52 and the consultant fee is 4. You don't know the incumbent's production cost, and at this point you have to decide whether to pay the consultant fee to learn the regulatory cost before you bid, or bid without learning. Imagine that you decide to bid without hiring the consultant. Thus, you have to bid without knowing the regulatory cost – all you know is that it is a whole number between 0 and 100, with each number being equally likely. You have to submit a bid to the buyer. You bid 110. After the incumbent also submits a bid, it is revealed that the incumbent bid 95.

**Question 3a:** Which supplier gets to make the item for the buyer (i.e., wins the auction)? (Incumbent)

**Question 3b:** How much does the buyer pay the incumbent to make the item? (110)

**Question 3c:** What is your profit? (0)

#### A.2.4 Comprehension Quiz 4

We consider the previous example except we change the incumbent's bid to 145.

**Question 4a:** Which supplier gets to make the item for the buyer (i.e., wins the auction)? (Entrant)

**Question 4b:** How much does the buyer pay you to make the item? (145)

*Since you have won the auction, you must hire the consultant to discover the regulatory cost. After you pay the consultant fee (4), you discover the regulatory cost is 80.*

**Question 4c:** What is your total cost to supply the item (including the consultant fee)? (136)

**Question 4d:** What is your profit? (9)

## A.3 Screenshots and Corresponding Verbal Instructions Read to Subjects by the Facilitator

This is the first screen that you will see (Figure A.1 is displayed on subjects' screens). You'll note that at the top it states your production cost. In this case, your production cost is 16. It also poses the main question for this screen — what would you do if the consultants fee was 1? On the left-hand side of the screen you have two calculators that you can use to test possible choices before you make a decision. The one on top corresponds to the case where you choose NOT to hire the consultant before the auction. It lists your production cost, the consultant fee, and reminds you that the regulatory cost is a whole number between 0 and 100, with each value being equally likely. You can then enter a bid and click "calculate". Let's have everyone enter a bid of 47 and click "calculate". You'll note that it gives you three numbers — first, your probability of winning the auction is 0.89 — that means that if you bid 47 your probability of winning the auction is 89%. The second number is your average profit if you win the auction. In this case, if you win the auction, you will, on average, make a profit of 41.53 — you won't get exactly 41.53, this is average over your possible profits if you win the auction. Finally, the third value is your average profit if you lose the auction — in this specific case, if you lose the auction your profit will be 0 because you won't have any revenue and you will have paid zero costs.

Now let's look at the second calculator (Figure A.2). This corresponds to the case where you choose to hire the consultant before the auction. Remember, when you choose to pay the consultant fee prior to the auction, you'll learn what the regulatory

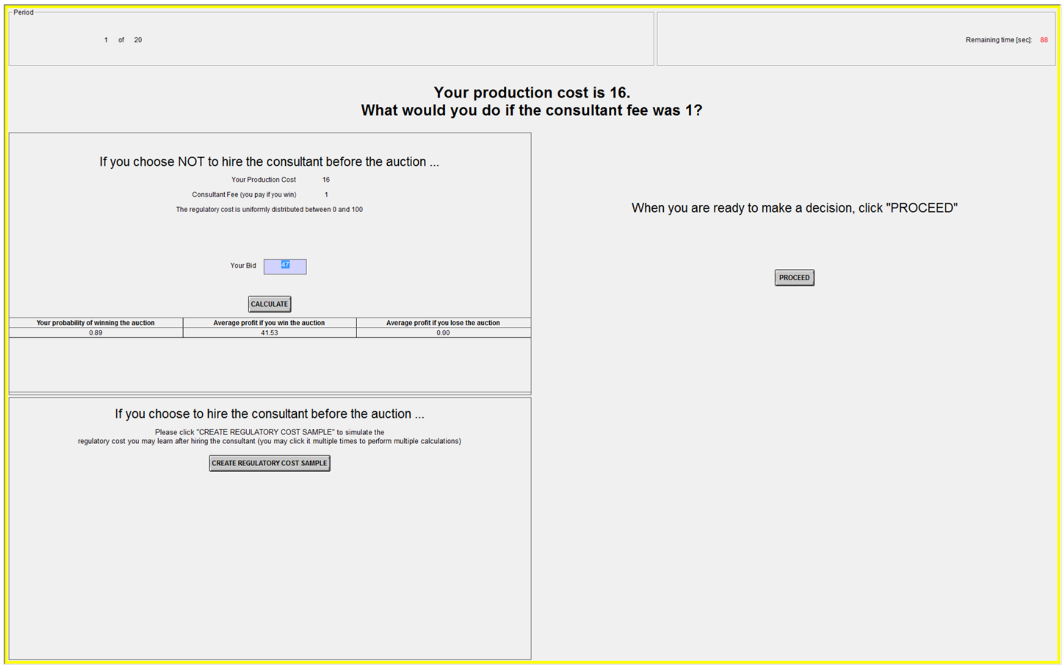



Figure A.1: Subjects' screen with the first decision support tool.

cost is before you have to bid. So, to get a sample regulatory cost realization, click the create regulatory cost sample button now. You'll see your production cost (16), the consultant fee that you already paid (1), and a sample regulatory cost appear — the sample regulatory cost will be different for everyone in the room, and it will change every time you click that create regulatory cost sample button. To see that happen, click "create regulatory cost sample" again and see it change right now. Okay, now we can enter a bid to use this calculator. Let's have everyone enter a bid of 100 and click the calculate button. You'll see the same three quantities be calculated as they were in the other calculator. After you've explored using this calculator for a minute and figured out if you would choose to pay the consultant fee prior to bidding, you can click "proceed" on the right hand side of the screen to enter your decision. Click "proceed" now. Now we can enter our decision. Lets have everyone choose to HIRE the consultant before bidding, and then click the red "submit decision" button.

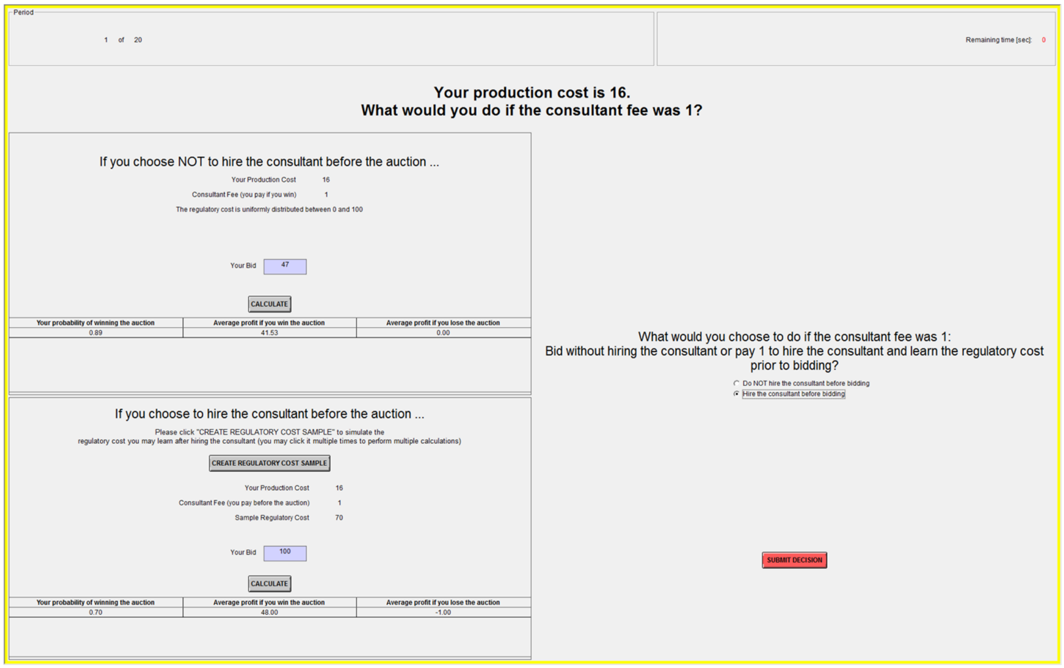



Figure A.2: The second decision support tool.

Okay, now you submitted your decision and you are taken to another screen (Figure A.3). You'll notice that the only thing that has changed here is now the consultant fee is equal to 4 instead of 1. At this point, you'll repeat the process for this new consultant fee. You can use the two calculators to the left and when you are ready to make a decision you click “proceed” on the right. Let's have everyone enter a random bid on the top calculator and click “calculate”, and then also create a regulatory cost sample on the bottom calculator. Also enter a bid on the bottom calculator as well — don't worry about what you enter here, the bids on the calculators don't count towards your payoff. Click “proceed” on the right and let's have everyone choose to not hire the consultant on this screen, and click “submit decision”.

You are now taken to a screen where the only thing that has changed again is the consultant fee (Figure A.4). Now, the consultant fee is 7, and it is asking whether you'd like to hire the consultant before bidding or wait until after the auction and

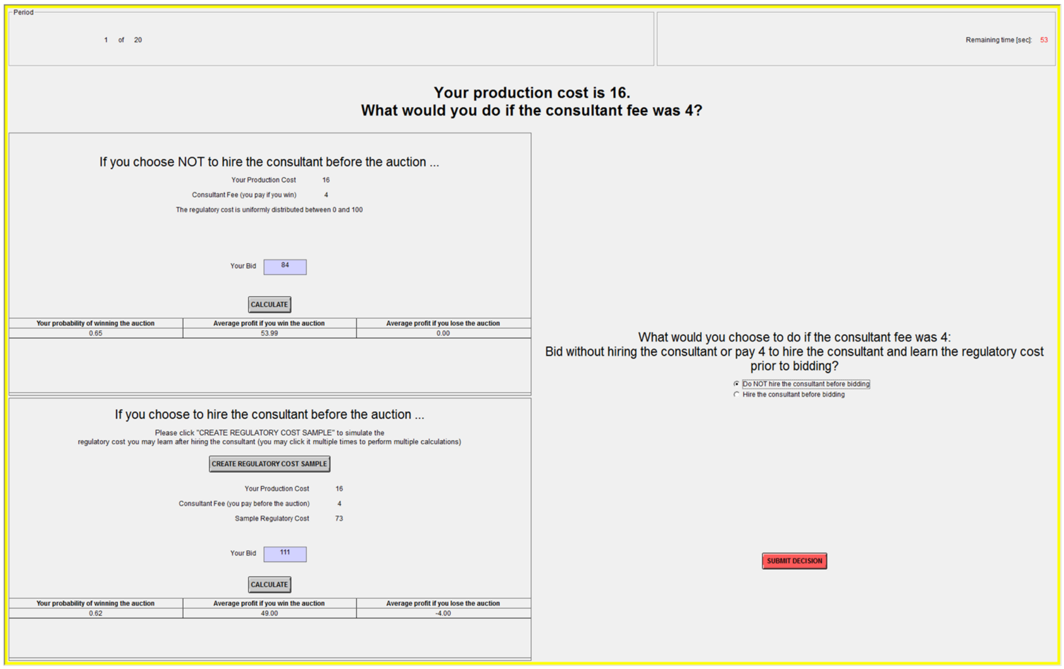



Figure A.3: Subjects' screen with a consultant fee of 4.

only hire him if you win the auction. You are free to use the calculators to the left for a minute, and when you're ready to enter a decision click "proceed" and let's have everyone choose to hire the consultant for this decision and click "submit decision".

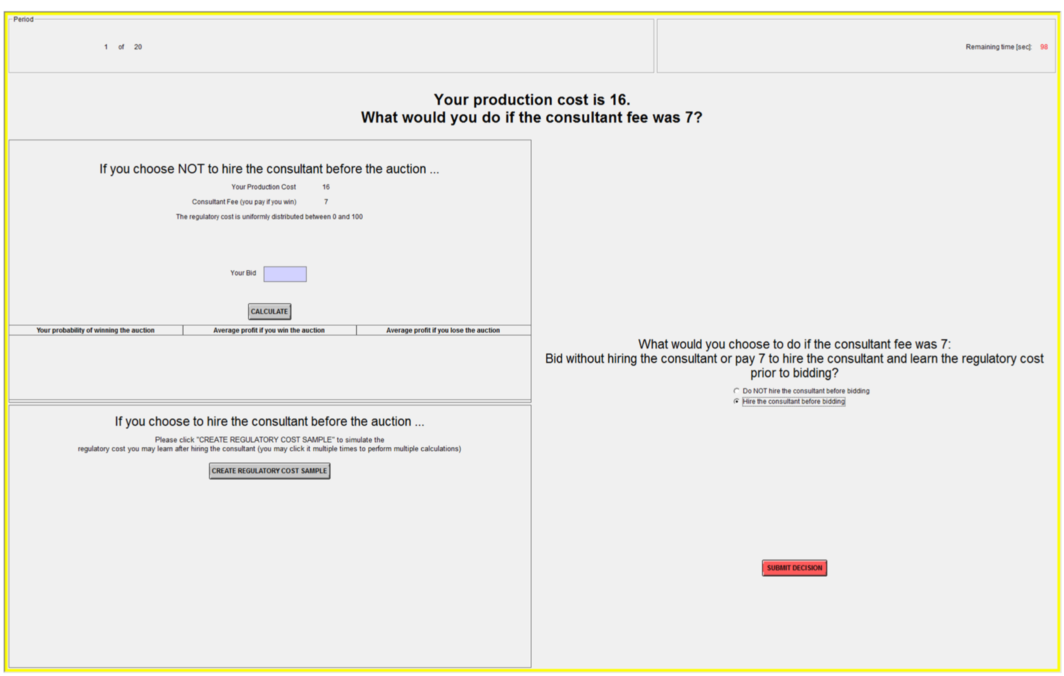



Figure A.4: Subjects' screen with a consultant fee of 7.

This will be the last screen that looks like this for a while (Figure A.5) — you'll notice that now the consultant fee is 10. Let's have everyone click "proceed" and choose NOT to hire the consultant before bidding and click "submit decision".

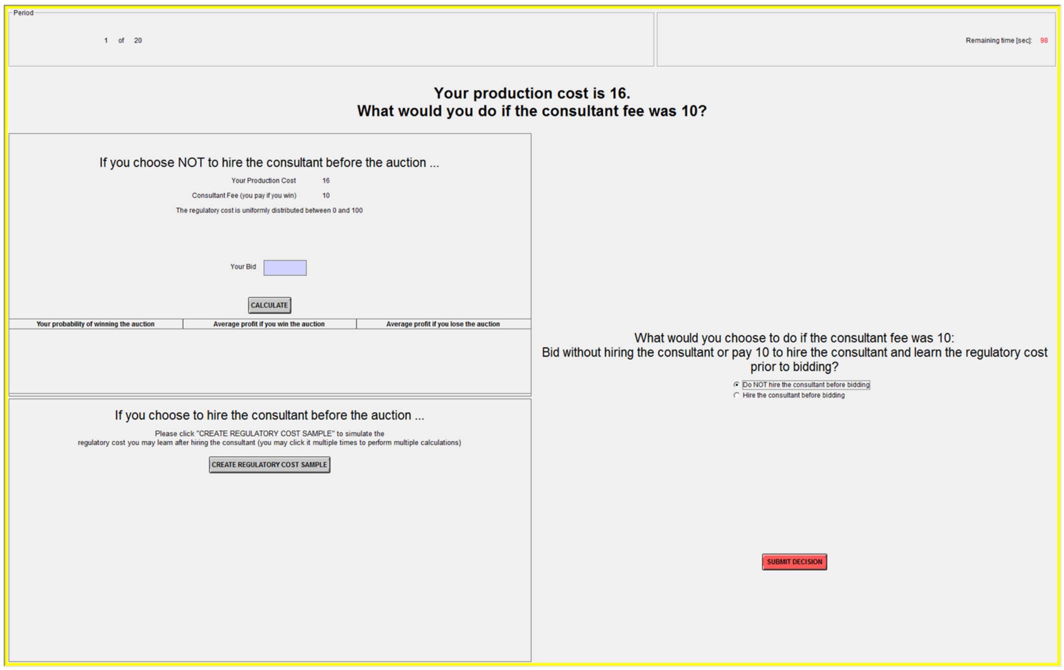



Figure A.5: Subjects' screen with a consultant fee of 10.

Now you'll see a screen where your decisions have been summarized (Figure A.6). At this point, if you have any regrets on the past four decisions that you made, you can change your mind and switch your answer. For this example we won't have you switch anything — just click "submit final decisions".

Now we'll actually get to play the game (Figure A.7)! At this point, the computer randomly selects one of the four hiring decisions you were just asked about — 1, 4, 7, or 10. In this case, it picks a consultant fee of 4. It'll automatically apply the decision that you submitted on the previous screen for a consultant fee of 4 once you click the "proceed" button. Go ahead and click "proceed".

For a consultant fee of 4, you chose NOT to hire the consultant before bidding (Figure A.8). So, the calculator that corresponds to the case where you do not hire

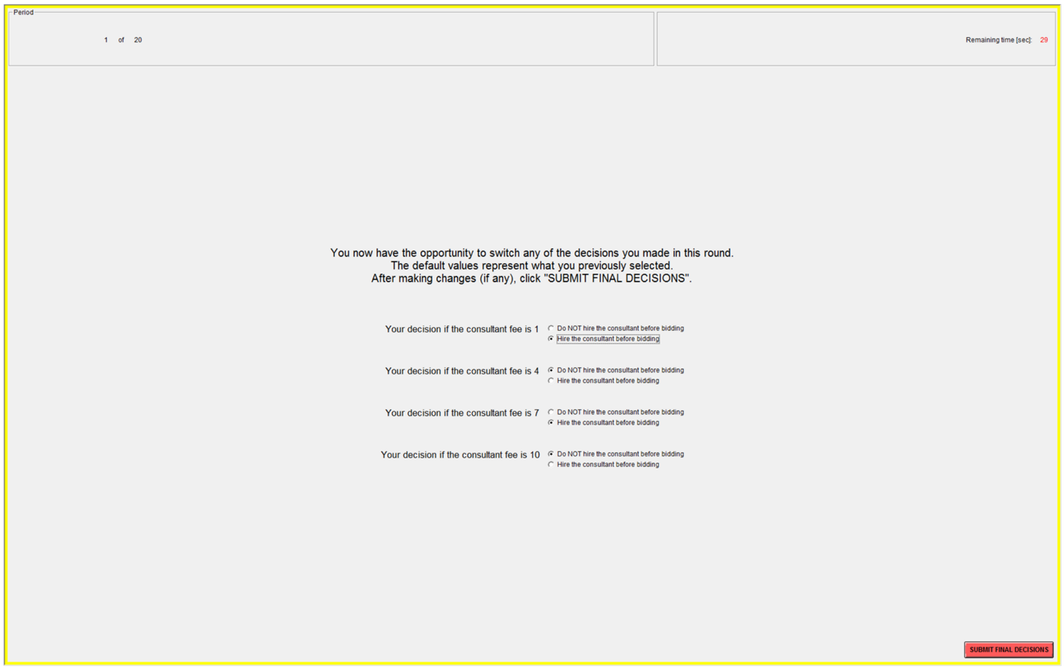



Figure A.6: Subjects view and have the option to change their selected decisions.

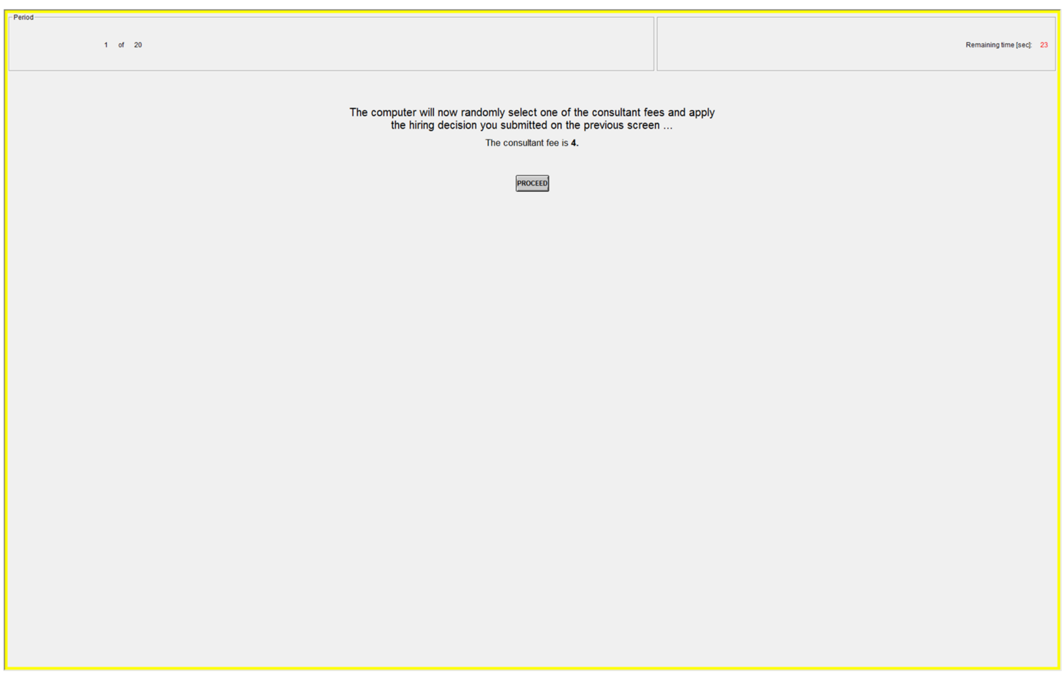



Figure A.7: A learning fee is randomly selected.

the consultant prior to the auction appears. You'll note that you will have to submit a bid to compete against the computer in the auction, so to help you come up with the best bid possible that can hopefully win you a lot of money, we've provided the calculator again. Enter a sample bid and click “calculate” to see the results. You can use this calculator as many times as you’d like. Once you are ready to enter your real bid for the auction, click “proceed” on the right hand side.

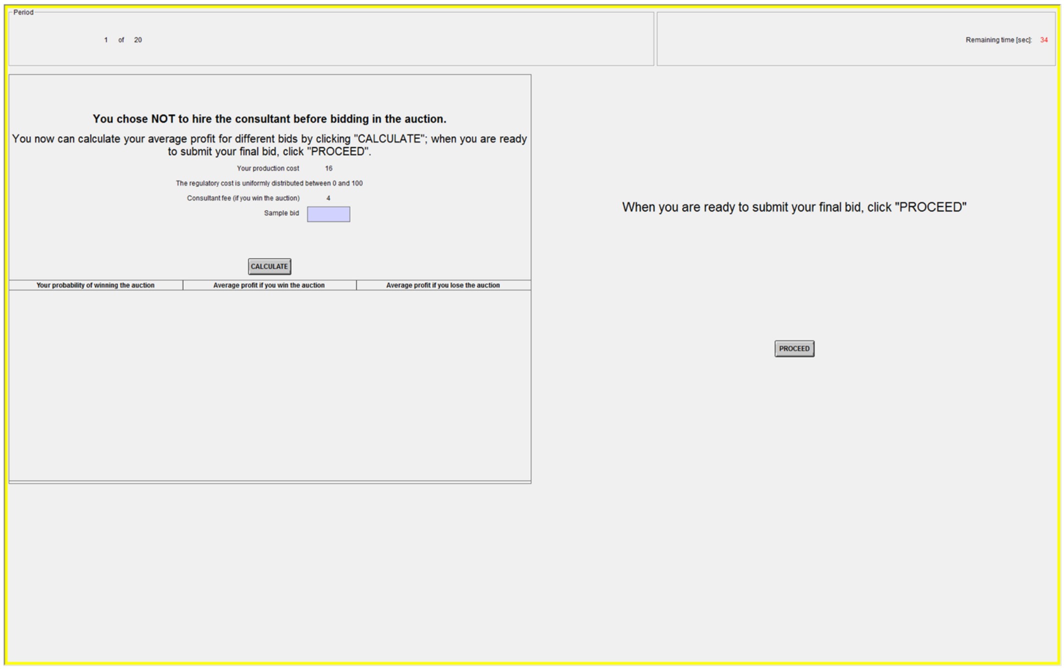



Figure A.8: The corresponding decision support tool appears.

In this case (Figure A.9), we’ll have everyone submit a bid of 47 — don’t worry, your payoff is not based on this example so don’t worry if you don’t think this is the best bid. So, enter 47 and click “submit bid”.

You’ll note that at this point the screen (Figure A.10) reveals the incumbent’s cost information and you can see that the incumbent had a production cost of 21, there is a common regulatory cost of 32, and the incumbent bid a total of 53. Now you can click “calculate profit” to see how you fared in the auction.

This screen (Figure A.11) now shows a summary and you can see that you won the auction! You’ll also note that while you made money in this auction, you made very little — your profit in this auction is 1. This was calculated by taking your revenue minus your costs, and your revenue was the incumbent’s bid (53) and your


Figure A.9: Subjects then enter their binding bid for the auction.

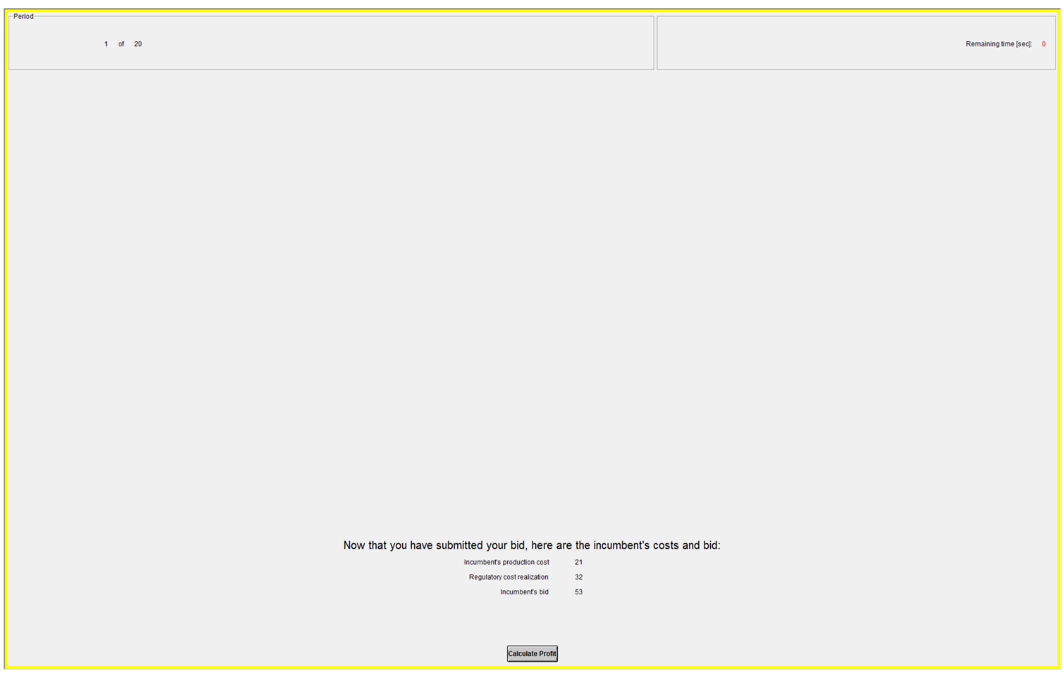



Figure A.10: The incumbent's private information is revealed after the subject submits his bid.

costs were the consultant fee of 4, the regulatory cost of 32, and your production cost of 16. Add all that up and your profit is 53 minus 52, or 1. Okay, now we're ready to begin the experiment. You'll play the same game that we just walked through 20 times. Don't worry, it'll actually go pretty fast as you get a feel for the calculator and the different questions. Make sure to take your time because your earnings will depend on your performance in the game  we'll select three random periods and pay you the average of what you earn in those three periods plus your $5 show-up fee. Let me know if you have any questions by raising your hand and you can go ahead and get started!

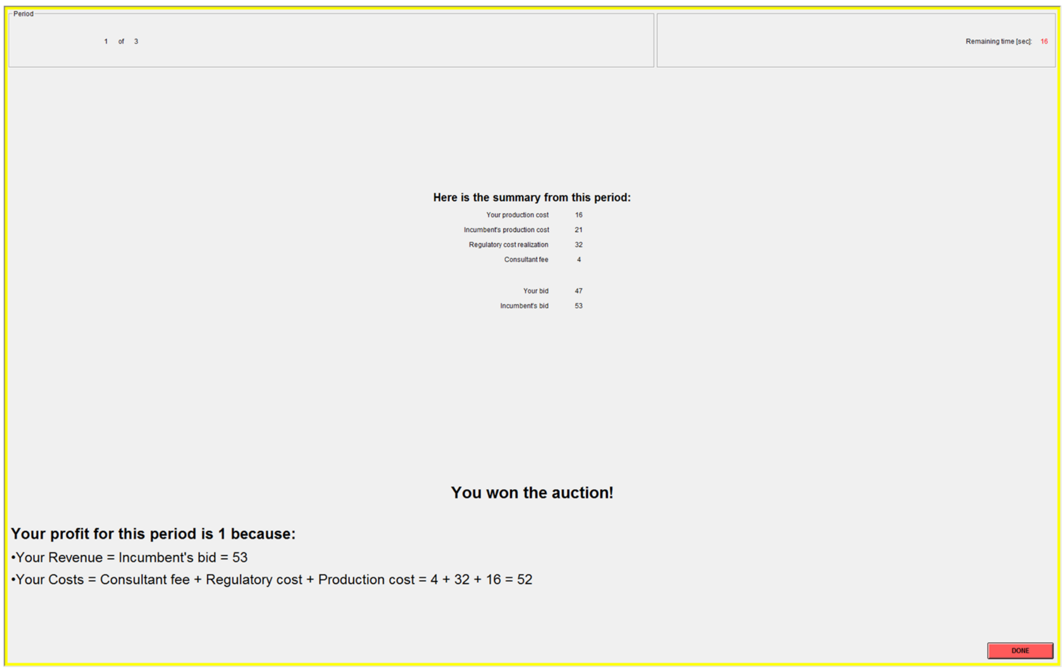



Figure A.11: A summary screen with the subject's profit for the period.

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